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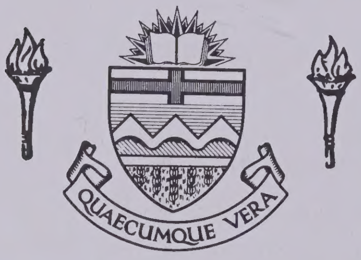

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TITLE OF THESIS BINARY DISTILLATION COLUMN CONTROL: EVALUATION OF DIGITAL CONTROL ALGORITHMS

DEGREE FOR WHICH THESIS WAS PRESENTED MASTER OF SCIENCE

YEAR THIS DEGREE GRANTED SPRING, 1982

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THE UNIVERSITY OF ALBERTA

BINARY DISTILLATION COLUMN CONTROL: EVALUATION OF DIGITAL CONTROL ALGORITHMS

BY

© HON WAH KAN

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES AND RESEARCH
IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE
OF MASTER OF SCIENCE
IN
PROCESS CONTROL

DEPARTMENT OF CHEMICAL ENGINEERING

EDMONTON, ALBERTA

SPRING, 1982

THE UNIVERSITY OF ALBERTA
FACULTY OF GRADUATE STUDIES AND RESEARCH

The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies and Research, for acceptance, a thesis entitled BINARY DISTILLATION COLUMN CONTROL: EVALUATION OF DIGITAL CONTROL ALGORITHMS submitted by Hon Wah Kan, B.Sc.(Engineering), in partial fulfilment of the requirements for the degree of MASTER OF SCIENCE in PROCESS CONTROL.

Abstract

The purpose of this project was an evaluation of the performance of the deadbeat, Dahlin and Smith predictor algorithms for bottom composition control of a binary distillation column. The control behaviour achieved using these algorithms was compared to that obtained using discrete proportional-integral (PI) and proportional-integral-derivative (PID) algorithms.

Although the distillation column exhibits highly nonlinear dynamic behaviour as well as time delay, first order plus time delay transfer function models were used to represent the dynamic behaviour of the distillation column for use in the design procedure for the deadbeat, Dahlin and Smith predictor algorithms.

Simulation studies of these algorithms were carried out using a nonlinear distillation column model. The simulation results showed that for the case of very small model errors, the deadbeat algorithm, the Dahlin algorithm and the Smith predictor were superior to the PI and PID algorithms for servo control operations. However, the performance of these algorithms, tuned by using conventional tuning methods, was inferior to that achieved using the PI and PID algorithms for the feed flow rate disturbance. Subsequently, an improved tuning procedure was utilized and with this procedure, the column control performance achieved with the deadbeat, Dahlin and Smith predictor algorithms was superior to that obtained using the PI and PID algorithms.

The experimental evaluation of the different control algorithms was conducted on a 22.9 cm diameter, eight-tray pilot scale distillation column unit interfaced with a distributed system of HP 1000 computers. An on-line process gas chromatograph was used to provide direct measurement of the bottom composition. The primary investigation was the performance of the Dahlin and Smith predictor algorithms for a -25% step change in feed flow rate to the column. From the experimental results, it was found that the control performance achieved using these algorithms tuned by using the improved tuning technique was much better than that of the PI algorithm whose poor performance was due to the significant amount of time delay present in the process. Use of the PID algorithm, gave performance that was close to that achieved using the Dahlin algorithm and the Smith predictor. For servo operations, employing the tuning constants established for regulatory control, the Dahlin algorithm provided the best and the most consistent performance for ±1% step changes in set point.

It should be noted from both the simulation and experimental results, that the significantly improved performance which resulted using the PID algorithm compared to that with the PI algorithm can be attributed to the presence of the derivative action. So for controlling time delay processes, since the PID algorithm is model independent, it should be used more frequently for industrial applications than at present.

Acknowledgement

The author would like to acknowledge the staff at the DACS Centre, instrument and mechanical shops for their support during the course of this project.

A special note of thanks is in order for Henry Lieuson for assisting the development of the nonlinear distillation column model.

Finally, the author wishes to express his sincere gratitude to Dr. R. K. Wood for his assistance and guidance in this project. Financial support from the National Science and Engineering Research Council for this project is also greatly appreciated.

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List of Symbols

Symbols for Control Algorithms

Symbol	Description
a_i	coefficients in the numerator polynomial of the digital controller transfer function D(z)
b_i	coefficients in the denominator polynomial of the digital controller transfer function D(z)
c_i	coefficients, unique to particular equation
C	controlled variable
D	transfer function of a digital controller
e	error = set point - measurement reading
E	error in s or z domains
f	coefficients, unique to particular equation
G	process transfer function
G_p	process transfer function
G_{zoh}	transfer function of a zero-order-hold device
H	transfer function of a measurement device
k	sample index
K	transfer function of the close loop response
K_C	proportional constant in PI or PID control algorithm
K_D	derivative constant in PID control algorithm
K_I	integral constant in PI or PID control algorithm
K_p	process gain
m	order of a polynomial
M	measurement time delay expressed as a number of sample intervals, $M = T_m/T$
n	order of a polynomial
N	total system time delays in number of sample intervals, $N = M + P$

P	process time delay in number of sample intervals, $P = T_d/T$
R	set point in s or z domains
s	Laplace domain variable
t	time domain variable
T	sample time
T_c	closed loop total system time-delay
T_d	process time delay
T_D	derivative time constant in PID control algorithm
T_I	integral time constant in PI or PID control algorithm
T_m	measurement time delay
T_p	process time constant
u	controller output
U	controller output in s or z domain
z	z-domain variable

Symbols for Distillation Column Model

Symbol	Description
A	system matrix, defined by component balance equations
B	system matrix, defined by mass and energy balance equations
Δt	integration time interval (s)
E	Murphree vapour efficiency
F	feed mass flow rate (g/s)
h	liquid enthalpy (KJ/g)
H	vapour enthalpy (KJ/g)
L	liquid mass flow rate (g/s)

Q_I	heat input (KJ/s)
Q_L	heat loss (KJ/s)
Q_R	reboiler duty (KJ/s)
R	reflux flow rate (g/s)
S	side stream mass flow rate (g/s)
V	vapour mass flow rate (g/s)
WT	liquid mass holdup in a stage (g)
x	liquid composition (wt.% methanol)
y	vapour composition (wt.% methanol)

Subscripts

i	initial value
f	final value
n	stage number

Superscripts

k	variable value at the k^{th} integration cycle
*	equilibrium composition

1. Introduction

1.1 Objectives

The availability of low cost digital computers with a high degree of reliability, particularly the new generation of process computers that are now available, is having a significant impact on computer utilization in the process industries. For control engineers, it means that more advanced control schemes and control algorithms can be implemented by the process computers. This project deals with an evaluation of different digital control algorithms, namely the deadbeat algorithm, the Dahlin algorithm, the discrete Smith predictor, and comparison with the discrete proportional-integral (PI) and proportional-integral-derivative (PID) algorithms.

In the implementation of digital control algorithms, some of the primary concerns in selecting a general digital control algorithm are:

1) the algorithm should easily be a standard software block of a direct digital control (DDC) package;
2) the algorithm should be easily programmed;
3) the computational efficiency of the algorithm should be high;
4) the output of the algorithm should be calculated only based on the present error, past errors and past outputs; and

5) the algorithm should be general enough that different control algorithms can easily adapt to its form.

In evaluation of the performance of different control algorithms, the primary concerns are:

1) the performance under regulatory control;
2) the ability of the algorithm to compensate for process time delay;
3) the simplicity of on-line tuning; and
4) the influence of model errors and nonlinearity on the performance of the control algorithm.

The experimental work of this project was carried out on the pilot scale binary distillation column in the Department of Chemical Engineering. Control of the distillation column is difficult, since it exhibits nonlinear behaviour as well as time delay. These process characteristics plus the increased time delay due to the use of a gas chromatograph for bottom composition analysis make the column a realistic system for the evaluation of the performance of different control algorithms.

1.2 Thesis Organization

This thesis is organized in the following manner: In Chapter 2, a brief literature survey on digital control algorithms is presented; the development of the various digital control algorithms is given in Chapter 3; Chapter 4 describes the development of a nonlinear binary distillation

column model; the results of the digital simulation studies on the performance of different control algorithms are presented in Chapter 5; implementation of the digital control algorithms is described in Chapter 6, as well as the results of the experimental evaluation of the control algorithms; finally, the overall conclusions and recommendations from this work are summarized in Chapter 7.

2. Literature Survey on Digital Control Algorithms

2.1 Introduction

With the flexibility provided by digital process computers, control engineers can now implement not only more sophisticated control strategies, such as different levels of supervisory control for plant-wide optimization, but use advanced control algorithms for low level control to achieve better process performance. In this chapter, a brief literature survey of the digital control algorithms, for single input single output feedback control systems, which are readily available for industrial applications will be discussed. The format of the discussion is based on the evolution of digital control applications in the process industries. The survey covers developments from the use of the digital equivalent of conventional control algorithms to the present involvement of designing digital control algorithms using sampled-data control theory. Tuning techniques for the algorithms cited in this chapter will also be discussed with emphasis on the tuning procedures for regulatory control applications.

2.2 Digital PI and PID Algorithms

The digital proportional-integral (PI) and proportional-integral-derivative (PID) control algorithms were the earliest digital control algorithms applied to control applications in process industries when the digital process comput-

ers were introduced for plant control. During the period from the early 60's to the mid 70's, methods of obtaining the digital equivalent of the conventional analog PI and PID controllers and the tuning techniques for these two digital control algorithms received the most attention.

2.2.1 Positional and Incremental Forms

There are two basic forms, namely the positional form and the incremental form (also known as the velocity form), of digital PI and PID control algorithms. The most commonly used positional form of an ideal digital PID control algorithm is described by the following equation:

$$u_k = K_c \left[e_k + \frac{T}{T_I} \sum_{i=1}^{i=k} e_i + \frac{T_D}{T} (e_k - e_{k-1}) \right] + u_{ss} \qquad (2.2.1)$$

Its counterpart, the incremental form is obtained by taking the difference between Equation 2.2.1 and the equation for the previous sample (k-1). The resulting expression is

$$\Delta u_k = K_c \left[(e_k - e_{k-1}) + \frac{T}{T_I} e_k + \frac{T_D}{T} (e_k - 2\, e_{k-1} + e_{k-2}) \right] \qquad (2.2.2)$$

In general, the incremental form of the ideal digital PID controller is preferred rather than the positional form because of its "bumpless" transfer and anti-reset windup features [Bibbero (1977), Bristol (1977), Desphande and Ash (1981), Smith (1972)].

Different approximation techniques for the integral

and/or derivative term(s) have been suggested [Bibbero (1977), Smith (1972), Verbruggen et al. (1975)] to improve the performance of the algorithm. A summary of the different forms of digital PID control algorithms, in the z-domain, that result from using different discrete integration techniques is presented by Verbruggen et al. (1975). Although it has been claimed that using different approximation techniques, such as the trapezoidal rule for integration [Bibbero (1977), Smith (1972)], the four point central difference formula for the derivative [Bibbero (1977)] would improve the operations of the algorithm, no comparison of these "improved" algorithms with the ideal digital PID (cf. Equations 2.2.1 and 2.2.2) has been undertaken to the author's knowledge.

Another variation from the ideal PID algorithm is the change of the feedback variable to the derivative term. Smith (1972) commented that "there is no real advantage in allowing the derivative mode to act on a change in set point signal", therefore, the feedback variable for the derivative term, as suggested by Smith, should be the measurement sequence rather than the error sequence. The advantage of the resultant algorithm is the elimination of a "kick" from the derivative action due to a set point change and the algorithm is essentially the same as the original form when it is applied to regulatory applications. Other considerations regarding implementation of digital PI or PID algorithms have been discussed in detail by Bristol (1977) and

Smith (1972), but some of the material, particularly that dealing with hardware limitations, is now out of date.

Despite the existence of various forms of digital PI and PID algorithms with practical enhancements, the digital PI and PID algorithms still most frequently used for comparison with the performance of control behaviour achieved using other control algorithms are those given by Equations 2.2.1 and 2.2.3.

2.2.2 Tuning Digital PI and PID Algorithms

The main advantage of using digital PI and PID controllers over the other digital control algorithms is that they are general purpose single loop controllers. However, fine tuning the PI and PID controllers to yield optimal control performance is not a simple task because of the necessary trial and error procedure. With the appearance of low cost digital computers, finding the optimal controller settings using a systematic approach can be performed through digital simulations. Lopez et al. (1967) proposed that error-integrals of the closed loop response of a control loop should be used as the tuning criteria for analog PI and PID controllers rather than the quarter decay ratio criterion as proposed by Ziegler and Nichols (1942). Three types of error-integral, namely the integral of squared error (ISE), the integral of the absolute value of the error (IAE) and the integral of time multiplied by the absolute value of the error (ITAE), were suggested as the criteria for adjusting

the controller settings of the analog PI and PID controllers. The characteristics of the different integrals and their applications were also discussed by Corripio et al. (1973) in a later publication. Through simulation studies, Lopez et al. (1967) were able to relate the parameters of a first order plus time delay transfer function model with the controller settings for analog PI and PID controllers which could be used to minimize the error-integrals and optimize the control performance. The correlation between the transfer function parameters and the controller constants were given in equation form. For digital PI and PID controllers, Lopez et al. (1969), using the same approach for the case of the analog PI and PID controllers, generated a set of tuning graphs correlating the model parameters and controller settings which could minimize the error-integrals. A similar approach has also been used by Roberts (1976). Unfortunately, convenient equations were not reduced from these graphs due to the additional parameter, the sampling time, present in the control algorithms. For a control loop in which the sampling effect is insignificant, i.e. the ratio of the sampling time to the most dominant process time constant is smaller than the ratio of the process time delay to the most dominant process time constant, correlations for the analog PI and PID controllers may be extended to the digital PI and PID controllers. Smith (1972) suggested the following procedure: add one half of the sampling time to the process time delay to compensate for the sampling effect and then apply

the correlations for the analog PI and PID controllers to obtain the controller settings for the digital PI and PID controllers. Other tuning approaches that do not use error-integral criteria have been employed. Chiu et al. (1973c) suggested the controller settings for PI and PID controllers be calculated using Dahlin's analogy that the desired closed loop response be specified and the parameters in the control algorithms be calculated from the closed loop characteristic equation (the Dahlin algorithm will be discussed in a later section). Vergruggen et al. (1975) summarized the coefficients of the discrete PI and PID controllers as a function of the ultimate gain and ultimate period of oscillation which are the Ziegler-Nichols closed loop criteria (1942), with adjustments for the sampled-data control system. Coefficients of the discrete PI and PID control algorithms according to the Haalman adjustments for analog PI and PID controllers have been reported by Verbruggen et al. (1975).

2.2.3 Choice of Sampling Time

In the digital PI and PID control algorithm, sampling time is an important factor which can affect the performance of the control algorithms significantly. Choosing the appropriate combination of the sampling time and the controller settings is a difficult task. In industrial practice, the sampling time for a control loop is chosen primarily according to the process conditions, e.g. one second sampling time for a flow loop [Smith (1972)], as opposed to the rigorous

analysis which is based on the stability of the control loop. The choice of sampling time from a practical point of view has been discussed by Smith (1972). Verbruggen et al. (1975) present a simple correlation for relating the choice of sampling time to the process time constant.

2.3 Discrete Smith Predictor

Time delays, such as transportation delay, measurement delay, are inherent in many chemical processes. When the time delay is significant in a control loop, i.e. the ratio of the time delay to the process time constant is relatively large, the control performance that is achieved using a PI or PID controller deteriorates. One of the special control schemes for controlling time delay processes that has received the most attention is the Smith predictor [Smith (1957,1959)]. The basic philosophy behind the development of the Smith predictor is to introduce an element into the control loop in such a way that the time delay element does not exist in the closed loop characteristic equation. Unfortunately because of the hardware implementation problem this scheme was not feasible until computers came into use in process control applications.

Experimental evaluation [Alevisakis and Seborg (1974), Buckley (1960), Doss (1974), Doss and Moore (1973), Lupfer and Oglesby (1962, 1961), Meyer et al. (1978), Prasad and Krishnaswamy (1975)] and simulation studies [Meyer et al. (1976), Nielsen (1969), Schleck and Hanesian (1978), Smith

and Groves (1973)] have demonstrated that for controlling time delay processes, the Smith Predictor can improve the control performance significantly as opposed to that achieved by using the conventional feedback controllers. Sensitivity analysis of modelling errors in the Smith predictor has also received considerable attention [Buckley (1960), Eisenberg (1967), Garland and Marshall (1975,1974), Marshall (1974)]. For practical implementation, Meyer et al. (1978) presented the derivation of the Smith predictor using time domain analysis while Deshpande and Ash (1981) developed the algorithm in the z-domain. Both approaches are well documented and the final equations are essentially equivalent. The discrete Smith predictor, in both cases, is in a form ready for programming, however, it should be noted that neither of these two approaches reduces the Smith predictor into the form of a single equation. Consequently, some ad hoc procedures are required for implementation of these equations with any general digital control package. Thesen (1980) presented an alternate derivation of the discrete Smith predictor, however, he concluded that the alternate form, which is more difficult to derive, does not yield any better control performance than that obtained using the discrete Smith predictor previously developed by Meyer et al. (1978).

For tuning the Smith predictor, the common approach is to assume that the model used in the algorithm is accurate so exact cancellation of the time delay term occurs. Conse-

quently the control constants in the PI controllers can be designed based on the effective closed loop characteristic equation or any correlations for PI control of processes not considered to contain time delays. In the experimental evaluation of the Smith predictor, Meyer et al. (1978) used the correlations for PI controllers suggested by Moore (1969) to obtain the initial tuning constants and the controller was then fine tuned for optimal performance.

2.4 Sampled-Data Control Algorithms

2.4.1 Direct Synthesis Method

While the digital equivalent of conventional analog controllers were implemented quite successfully on digital process control computers, digital control algorithms designed from an entirely different approach was under investigation. Koppel (1966) claimed that "there is no real reason to retain the proportional-integral or proportional-integral-derivative forms in direct digital compensation. These forms were developed for analog instruments. The greater flexibility made possible by use of compensation should be utilized in designing digital algorithms". The particular design method for digital or sampled-data control systems suggested by Koppel was the direct synthesis method developed by Ragazzini and Franklin (1958).

In the design procedure, using the direct synthesis method, requires that the transfer function of the process be known, then the controller can be obtained through the

manipulation of the overall transfer function providing the transfer function of the desired closed loop behavior is specified. Applications of this design procedure have been presented in varying degrees of detail by Badavas (1981), Chiu (1971), Chiu et al. (1973c), Condon and Smith (1977b), Dahlin (1968a), Deshpande and Ash (1981), Koppel (1966), and Lane (1970). The major advantages of using this design technique are its simplicity and flexibility, i.e. different control algorithms can be synthesized depending on the specification of the transfer function for the closed loop response.

It should be also noted that since the control algorithms designed using the direct synthesis method begins with a discrete model established for a particular sample interval, the performance of the control algorithms is affected by whether the discrete transfer function model, which is sample interval dependent, represents the actual process fairly [Jury (1958), Kuo (1977), Ragazzini and Franklin (1958)]

2.4.2 Deadbeat Control Algorithm

The deadbeat control algorithm is synthesized using the direct synthesis method by specifying the transfer function for the closed loop response to a step change in set point as $K(z) = z^{-n-1}$, where n is the number of sample intervals due to the time delay of the process and 1 designates the time delay due to sampling. The physical interpretation of

the above transfer function is that at the n+1th sampling instant after the introduction of a step change in set point, the deadbeat control algorithm will bring the controlled variable to the desired set point and will remain at the set point for all subsequent sampling instants. Although simulation results [Chiu (1971), Koppel (1966), Smith (1972)] were promising, however experimental results reported by Uronen and Yliniemi (1977) have demonstrated that the deadbeat control algorithm did not provide as satisfactory performance as did the digital PI and PID control algorithms. Application of the deadbeat control algorithm in the process industries is also not popular primarily due to the fact that it lacks convenient on-line tuning parameter(s) to adjust for changes in process conditions.

2.4.3 Dahlin Control Algorithm

A digital control algorithm which is gradually gaining industrial acceptance is that developed by Dahlin (1968a). This single input single output algorithm was also proposed for the control of multivariable systems when the control system is completely decoupled [Dahlin (1968b)], however this multivariable control scheme did not receive much attention probably due to the fact that the frequency domain design technique for multivariable control systems was dominant at the period. In the subsequent discussion, only the single input single output version of the Dahlin algorithm will be presented.

The Dahlin algorithm is also synthesized via the direct synthesis method. In this case, the transfer function for the closed loop response to a step change in set point is specified to be first order plus time delay. With the manipulation of the time constant, λ in the closed loop response transfer function, desired performance can be obtained. Also, manipulation of this variable provides on-line tuning of the control algorithm for different process conditions. The ringing free form of the Dahlin algorithm can be obtained by removing poles that are close to the unit circle [Chiu et al. (1973a), Dahlin (1968a)]. It should be noted that this ringing free form of the algorithm has the same structure of the digital PI or PID control algorithm if a first or second order plus time delay process transfer function is used respectively.

Simulation results [Badavas (1981), Chiu (1971), Chiu et al (1973a), Condon and Smith (1977a, 1977b), Smith (1972)] have shown that the performance of the Dahlin algorithm for both servo and regulatory control operations is comparable to that achieved by using the digital PID control algorithm. For a control system with a significant time delay, the performance using the Dahlin algorithm is found to be superior to the performance that is possible using a digital PID control algorithm. On the other hand, experimental results obtained by Uronen and Yliniemi (1977), showed that the performance of the Dahlin algorithm is rather sluggish when it is used for regulatory control. These conclusions

however are subject to the specific control systems being considered since a general analysis on the performance of the control algorithm, from a theorectical approach, to the author's knowledge does not exist. Sensitivity analysis to demonstrate the effect of inaccurate model parameters used in the Dahlin algorithm have been undertaken by Badavas (1981) and Condon and Smith (1977b) using digital simulation. From the simulated results, Condon and Smith observed that the performance of the Dahlin algorithm for servo operation is improved noticeably if the process time constant or the process time delay is over- estimated. However, an inappropriate value of the process time delay will cause the control system to be unstable. The sensitivity analysis study by Badavas reported stability limits which correlate with the parameters in the process transfer function from frequency domain considerations.

On-line tuning the Dahlin algorithm is quite straightforward. After obtaining the best estimated process model parameters, the initial value of λ is set to be the same in value as the process time constant. The desired performance can then be achieved by adjusting λ according to observations of the closed loop response.

2.4.4 Other Sampled-Data Control Algorithms

An algorithm which can be considered as a variation of the Dahlin algorithm is that reported by Higham (1968) and Jones (1978). The primary difference between the Dahlin

algorithm and the one of Higham is that the incremental output is calculated in Higham's algorithm as opposed to positional output being calculated in the Dahlin algorithm. Tsing et al. (1979) proposed another variation of the Dahlin algorithm based on Higham's analogy; instead of using a transfer function to represent the process, Tsing and coworkers suggested the use of the actual data of the process response to a set point change in their algorithm. The resultant algorithm is in terms of the present error term and the incremental output sequence. Both the proposed algorithms provide a single on-line tuning parameter similar to that in the Dahlin algorithm.

The Kalman algorithm [Chiu (1971), Chiu et al. (1973b), Smith (1972), Uronen and Yliniemi (1977)] is designed on the basis of a specification of both the responses of the manipulated and controlled variables. Simulation studies by Chiu (1971), Chiu et al (1973b), Smith (1972) and experimental evaluation by Uronene and Yliniemi (1977) have shown that the Kalman algorithm will also provide satisfactory performance. However, the Kalman algorithm suffers form the same disadvantage as the deadbeat algorithm, namely that it is an algorithm that does not contain parameters suitable for on-line tuning.

In the design procedure for the different control algorithms that haven been discussed, a load disturbance to the system is not considered although some algorithms do have an on-line tuning parameter to adjust for changes in process

conditions. Mutharasan et al. (1978) proposed an algorithm which can compensate for both set point and load changes. The design procedure involves determination of values for the manipulated variable to achieve a desired response in a manner which is analogous to the direct synthesis method. The control algorithm is also a simple recursive equation of input and output sequence. Although the algorithm is a steady state feedforward type of control algorithm, it should be possible to easily extend to a predictive type control scheme.

2.5 Future Trends

From the preceding discussion, it can be concluded that a control algorithm designed with at least some knowledge of the process, i e. a mathematical model which represents the dynamics of the process to be controlled is included in the design procedure, can provide better performance than the conventional PI or PID control algorithms. On the other hand, it is also understood that the use of an inaccurate model in the control algorithm will cause the performance to deteriorate significantly as well as tend to cause system instability. For these reasons, adaptive control schemes become very attractive to control engineers.

One of the adaptive control algorithms which has received considerable attention in recent years is the self-tuning controller. Application of self-tuning controller on distillation column can be found in Lieusion (1980).

3. Digital Control Algorithms

3.1 Introduction

In recent years, due to significant hardware improvements, there has been a rapid growth in the use of digital computers for process control. Although control engineers can now implement without difficulty more advanced control schemes or control algorithms, most of the control loops in industry still employ only conventional single variable feedback control using PI or PID control algorithms. Part of the reason for this situation arises from the fact that many of the advanced control algorithms designed for continuous control systems often require an ad hoc approach for a digital system implementation.

In this chapter, a general purpose digital control algorithm of the form

$$D(z) = \frac{U(z)}{E(z)} = \frac{a_0 + a_1 z^{-1} + . . + a_{n-1} z^{-n+1} + a_n z^{-n}}{b_0 + b_1 z^{-1} + . . + b_{m-1} z^{-m+1} + b_m z^{-m}} \qquad (3.1.1)$$

will be used for presentation of the different algorithms.

Advantages of using the above algorithm for computer process control are:

1) it can be easily programmed;
2) the computational efficiency is high, because it involves only simple arithmetic operations;
3) the control output U is calculated based on the present error, past errors and past outputs; and

4) almost all control laws can be expressed using this form of algorithm.

Since a system operated under computer control is sampled-data in nature, the mathematical derivation involves manipulation in the z-domain. The direct synthesis method is chosen in this work for designing digital control algorithms because of its simplicity. This technique will be presented in the next section. The digital form of the deadbeat and Dahlin algorithms, which are derived by this technique are discussed in Sections 3.3 and 3.4 respectively. Since the Smith predictor has gained acceptance in industry for the control of processes containing time delays, the discrete form of this well known algorithm is given in Section 3.5. In the last section of this chapter, Section 3.6, the incremental form of the PID algorithm is presented.

3.2 Direct Synthesis Method

The direct synthesis method is a simple and straightforward design procedure. This method can be applied to either continuous or sampled-data control systems. For the control system shown in Figure 3.2.1, the closed loop transfer function in either the s-domain or the z-domain is described by the following equation:

$$\frac{C}{R} = \frac{D\,G}{1 + D\,G} \qquad (3.2.1)$$

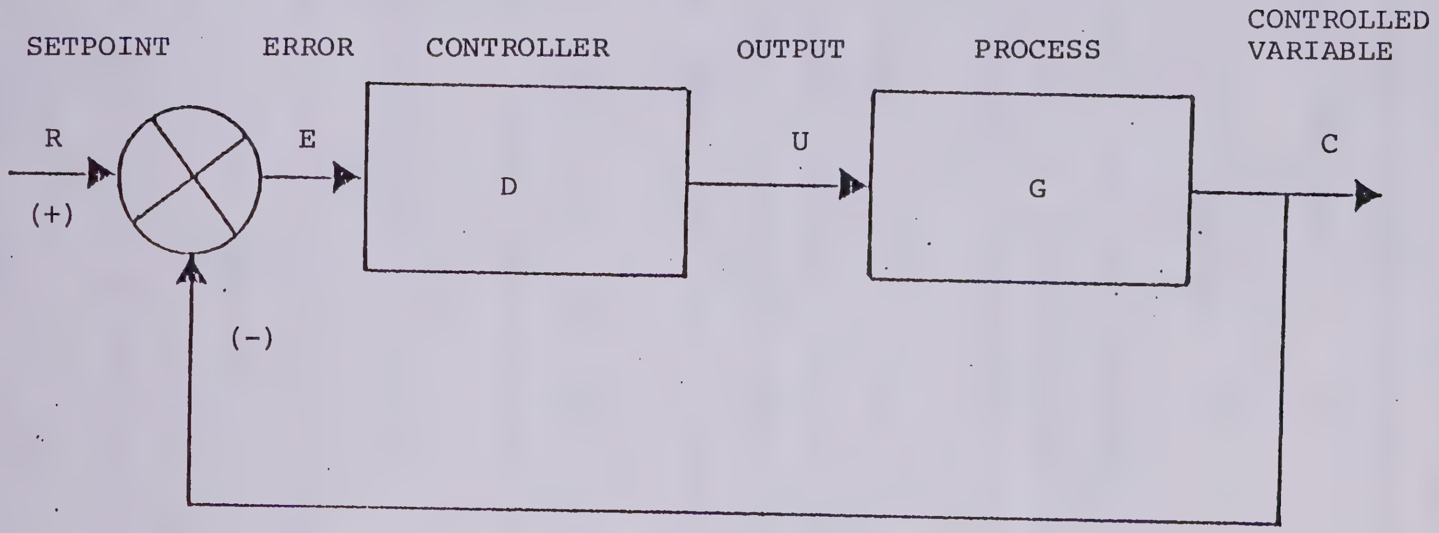

SETPOINT
ERROR
CONTROLLER
OUTPUT
PROCESS
CONTROLLED VARIABLE
R
(+)
E
(-)
D
U
G
C

Figure 3.2.1 Control System with Unity Feedback

Assuming that the transfer functions G and K(=C/R) are known, then the expression for the controller D is given by the following equation:

$$D = \frac{U}{E} = \frac{1}{G} \frac{K}{1 - K} \qquad (3.2.2)$$

It can be seen from Equation 3.2 2 that different control algorithms can be established depending upon the choice of K as selected by the designer for a particular application.

The direct synthesis method can also be extended to control systems which do not have unity feedback, for instance, the control system shown in Figure 3.2.2 contains a measurement device which has a transfer function other than unity.

The closed loop transfer function of this system expressed in z-domain representation is:

$$\frac{C(z)}{R(z)} = \frac{D(z)\ G(z)}{1 + D(z)\ G(z)\ H(z)} \qquad (3.2.3)$$

where

$$G(z) = \mathcal{Z}[G_{zoh}(s)\ G_p(s)] \qquad (3.2.4)$$

$$H(z) = \mathcal{Z}[H(s)] \qquad (3.2.5)$$

So it follows that the transfer function of the digital controller D(z) derived by the direct synthesis method is:

$$D(z) = \frac{U(z)}{E(z)} = \frac{1}{G(z)} \frac{K(z)}{1 - K(z)\ H(z)} \qquad (3.2.6)$$

where

$$K(z) = \frac{C(z)}{R(z)} \qquad (3.2.7)$$

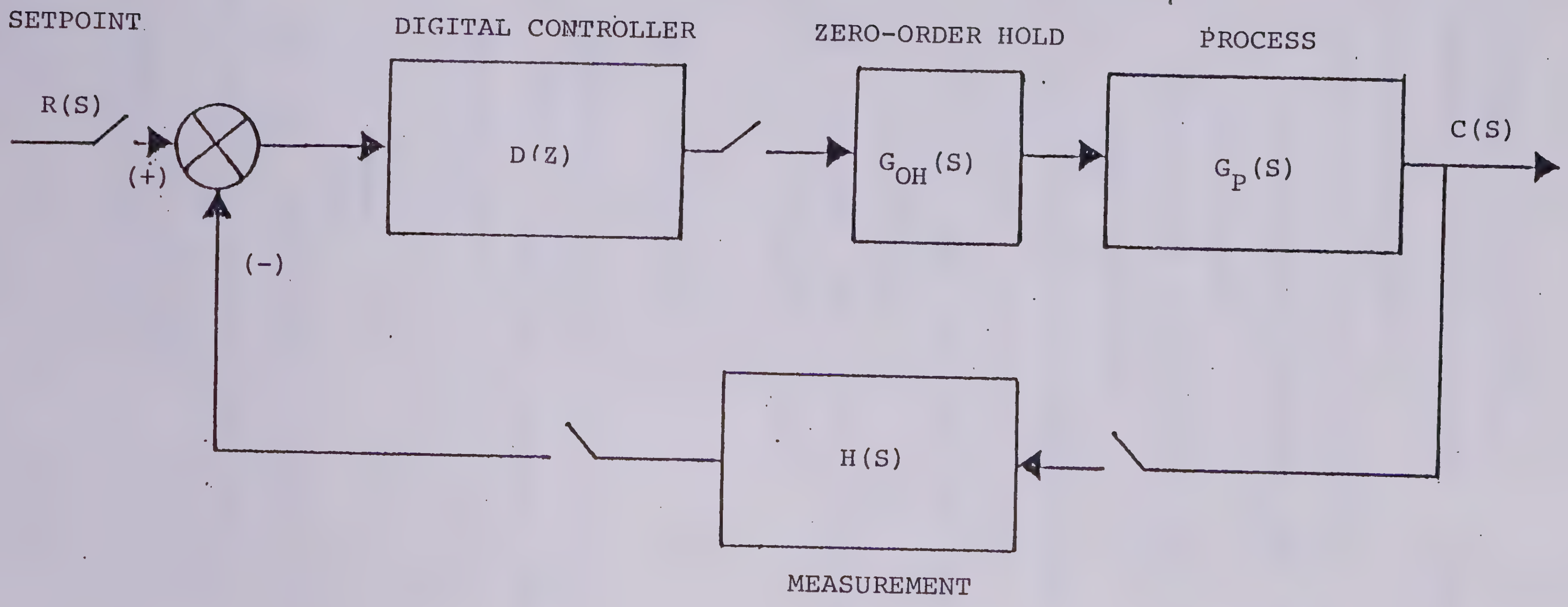

SETPOINT
R(S)
(+)
(-)
DIGITAL CONTROLLER
D(Z)
ZERO-ORDER HOLD
$G_{OH}(S)$
PROCESS
$G_P(S)$
C(S)
H(S)
MEASUREMENT

Figure 3.2.2 Sampled-Data Control System with Non-Unity Feedback

3.3 Deadbeat Control Algorithm

Deadbeat or minimal response is one which satisfies the following criteria (28):

1) The system must have zero steady-state error at the sampling instants for the specified input test signal.
2) The rise time should equal a minimum number of sampling periods.
3) The settling time, measured at the sampling instants, should be finite.
4) D(z), G(z) and C(z)/R(z) must all be physically realizable.

For a minimal phase system, the deadbeat response to a step input in set point is (28):

$$K(z) = \frac{C(z)}{R(z)} = z^{-1} \tag{3.3.1}$$

However for a system with a process time delay which is greater than or equal to P sampling intervals but less than P+1 sampling intervals, the response is:

$$K(z) = \frac{C(z)}{R(z)} = z^{-P-1} \tag{3.3.2}$$

For the sampled-data control system illustrated in Figure 3.2.2 with transfer functions:

$$G_p(s) = \frac{K_p \exp(-T_d s)}{T_p s + 1} \tag{3.3.3}$$

$$G_{zoh}(s) = \frac{1 - \exp(-Ts)}{s} \qquad (3.3.4)$$

$$H(s) = \exp(-T_m s) \qquad (3.3.5)$$

where K_p = process gain

T_p = process time constant

T_d = process time delay

T_m = measurement time delay

T = sampling time

Substitution of Equations 3.3.3 and 3.3.4 into Equation 3.2.4, yields

$$G(z) = \frac{K_p\ (c_1 + c_2 z^{-1})\ z^{-P-1}}{(1 - f_1 z^{-1})} \qquad (3.3.6)$$

where $c_1 = 1 - f_2$

$c_2 = f_2 - f_1$

$f_1 = \exp(-T/T_p)$

$f_2 = \exp(-m_p T/T_p)$

$m_p = 1 - T_d/T + P$

$P = T_d/T$ (integer)

For a measurement device with a transfer function given by Equation 3.3.5, the z-domain representation is:

$$H(z) = z^{-M}$$

where $M = T_m/T$ (integer)

For the transfer functions defined by Equations 3.2 6, 3.3.2, 3.3.6 and 3.3.7, use of the direct synthesis method gives the deadbeat control algorithm listed in Table 3.3.1.

Table 3.3.1

DEADBEAT CONTROL ALGORITHM

$$D(z) = \frac{U(z)}{E(z)} = \frac{a_0 + a_1 z^{-1}}{b_0 + b_1 z^{-1} + b_{n+1} z^{-N-1} + b_{n+2} z^{-N-2}} \quad (3.3.8)$$

$$u(k) = \frac{1}{b_0} [a_0 e(k) + a_1 e(k-1) - b_1 u(k-1) - b_{n+1} u(k-N-1) - b_{n+2} u(k-N\ 2)] \quad (3.3.9)$$

where $a_0 = 1$

$a_1 = -f_1$

$b_0 = Kpc1$

$b_1 = K_p c_2$

$b_{N+1} = K_p c_1$

$b_{N+2} = K_p c_2$

$f_1 = \exp(-T/T_p)$

$f_2 = \exp(-m_p T/T_p)$

$c_1 = 1 - f_1$

$c_2 = f_2 - f_1$

$m_p = 1 - Td/T + P$

$P = T_d/T$ (integer)

$M = T_m/T$ (integer)

$N = P + M$

3.4 Dahlin Algorithm

For most industrial applications, deadbeat response is ideal but usually not realistic because of process conditions. Furthermore, the deadbeat algorithm suffers from the fact that it does not have any provision for convenient on-line tuning of parameters. An algorithm that contains a single parameter that can be conveniently adjusted on-line is that of Dahlin (15). Dahlin proposed that the closed loop response of a control system for a step change in set point should behave like a continuous first order plus time delay process with the time constant of the closed loop transfer function being the on-line tuning parameter. The closed loop system response, for a system controlled by the Dahlin algorithms, is given by

$$\frac{C(s)}{R(s)} = \frac{\exp(-T_c s)}{\lambda s + 1} \tag{3.4.1}$$

in the s domain, and by

$$\frac{C(z)}{R(z)} = \frac{\mathcal{Z}\left[\dfrac{\exp(-T_c s)}{\lambda s + 1} \dfrac{1}{s}\right]}{\mathcal{Z}\left[\dfrac{1}{s}\right]} \tag{3.4.2}$$

in the z-domain. In Equation 3.4.2, T_c is the time delay in the closed loop response and λ is the time constant of the closed loop response which is the tuning parameter.

Since the controller must be realizable and must not require the prediction of future inputs or outputs, T_c in Equation 3.4.2 must be chosen no smaller than the value T_d

in Equation 3.3.3. For the limiting case, Equation 3.4.2 becomes:

$$K(z) = \frac{K_p\ (c_1 + c_2 z^{-1})\ z^{-P-1}}{(1 - f_1 z^{-1})} \qquad (3.4.3)$$

where $c_1 = 1 - f_2$

$c_2 = f_2 - f_1$

$f_1 = \exp(-T/\lambda)$

$f_2 = \exp(\ m_p\ T/\lambda)$

$m_p = 1 - T_d/T + P$

$P = Td/T$

For the sampled-data control system considered in Section 3.2, applying the direct synthesis method using the transfer functions defined by Equations 3.2.7, 3.3.6, 3.3.7 and 3.4.3, the Dahlin control algorithm can be obtained. The Dahlin algorithm derived by this procedure is given in Table 3.4.1.

Table 3.4.1

DAHLIN ALGORITHM

$$D(z) = \frac{U(z)}{E(z)} = \frac{a_0 + a_1 z^{-1} + a_2 z^{-2}}{b_0 + b_1 z^{-1} + b_2 z^{-2} + b_{N+1} z^{-N-1} + b_{N+2} z^{-N-2} + b_{N+3} z^{-N\ 3}} \qquad (3.4\ 4)$$

$$u(k) = \frac{1}{b_0}\,[a_0e(k) + a_1e(k-1) + a_2e(k-2) - b_1u(k-1) - b_2u(k-2) - b_{N+1}u(k-N-1) - b_{N+2}u(k-N-2) - b_{N+3}u(k-N\ 3)] \qquad (3.4.5)$$

where $a_0 = c_1$

$a_1 = c_2 - c_1f_3$

$a_2 = -c_2f_3$

$b_0 = K_pc_3$

$b_1 = K_p(c_4 - c_3c_1)$

$b_2 = -K_pc_4f_1$

$b_{N+1} = -K_pc_3c_1$

$b_{N+2} = -K_p(c_4c_1 + c_2c_3)$

$b_{N+3} = K_pc_4c_2$

$c_1 = 1 - f_2$

$c_2 = f_2 - f_1$

$c_3 = 1 - f_4$

$c_4 = f_4 - f_3$

$f_1 = \exp(-T/\lambda)$

$f2 = \exp(-m_p T/\lambda)$

$f3 = \exp(-T/Tp)$

$f4 = \exp(-m_p/Tp)$

$m_p = 1 - T_d/T + P$

$P = T_d/T$

$M = T_m/T$

$N = P + M$

3.5 Discrete Smith Predictor

The Smith predictor is well known for its ability to improve the control performance of processes that exhibit a significant time delay. The derivation of the Smith predictor has been given by numerous different workers (cf Chapter 2), but only for continuous systems. In this section, the discrete form of the Smith predictor is derived. The block diagram representation of the Smith predictor for continuous and sampled-data control systems is given in Figures 3.5.1 and 3.5.2 respectively.

In order to simplify the derivation of the discrete Smith predictor, it is convenient to use a different block diagram than that given in Figure 3.5.2. By block diagram reduction, the block diagram shown in Figure 3.5.2 can be modified to that shown in Figure 3.5.3.

From Figure 3.5.3, it follows that the expression for the discrete Smith predictor is

$$D(z) = \frac{D_1(z)}{1 + D_1(z)\, D_2(z)} \tag{3.5.1}$$

with $D_1(z)$, the discrete PID algorithm, given by

$$D_1(z) = \frac{a_0' + a_1' z^{-1} + a_2' z^{-2}}{1 - z^{-1}} \tag{3.5.2}$$

where $a_0' = K_C + K_I + K_D$

$a_1' = -(K_I + 2K_D)$

$a_2' = K_D$

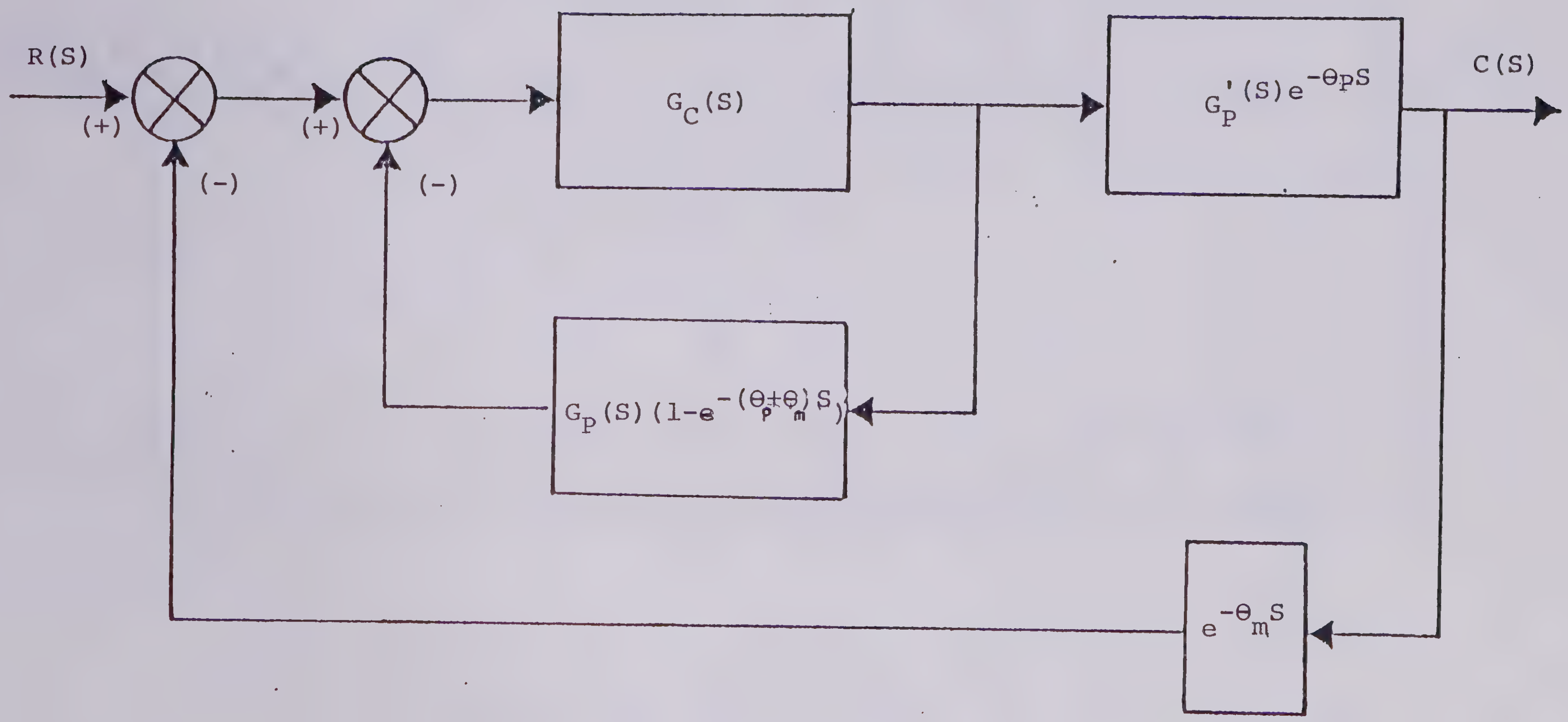

R(S)
(+)
(-)
(+)
(-)
$G_C(S)$
$G_P'(S)e^{-\theta_P S}$
C(S)
$G_P(S)(1-e^{-(\theta_p+\theta_m)S})$
$e^{-\theta_m S}$

Figure 3.5.1 Block Diagram Representation of the Smith Predictor for a Continuous Control System

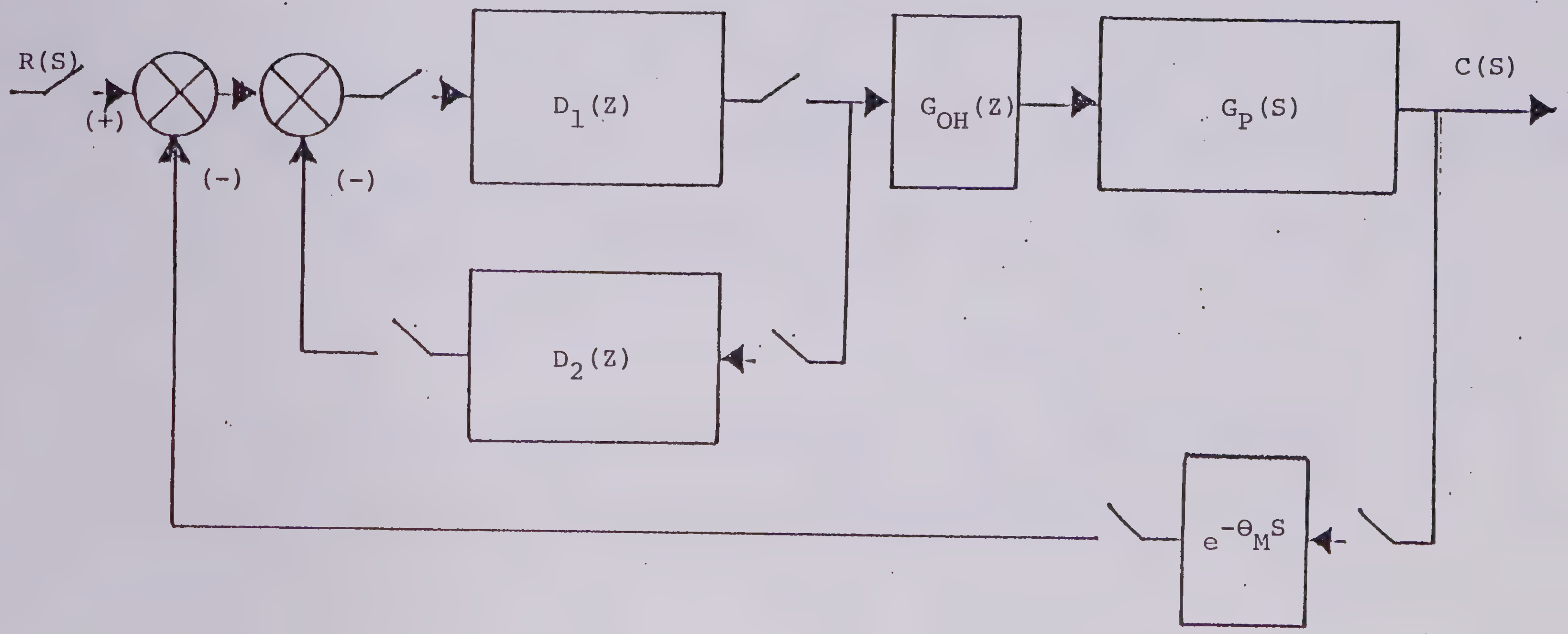

R(S)
(+)
(-)
(-)
$D_1(Z)$
$D_2(Z)$
$G_{OH}(Z)$
$G_P(S)$
C(S)
$e^{-\theta_M S}$

Figure 3.5.2 Block Diagram Representation of the Smith Predictor for a Sampled-Data Control System

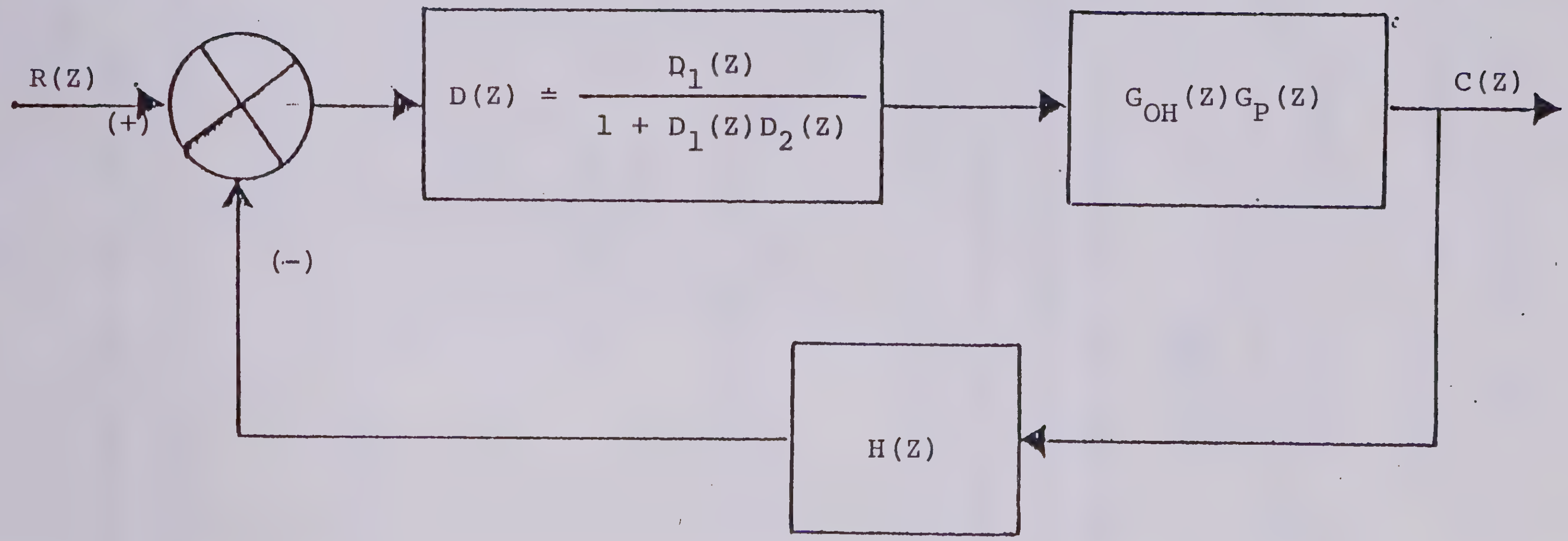

R(Z)
(+)
(−)
$D(Z) \doteq \frac{D_1(Z)}{1 + D_1(Z)D_2(Z)}$
$G_{OH}(Z)G_P(Z)$
C(Z)
H(Z)

Figure 3.5.3 Block Diagram Representation of the Discrete Smith Predictor Control Scheme

and $D_2(z)$, the time delay compensation part of the Smith predictor, expressed as

$$D_2(z) = \frac{\mathcal{Z}[G_p(s)\ (1 - \exp[-(T_d + T_m)s]\ \frac{1}{s})]}{\mathcal{Z}[\frac{1}{s}]} \qquad (3.5.3)$$

where $G_p(s)$ is $[K_p/(T_d s + 1)]$, the process transfer function (cf Equation 3.3.3) without the time delay element. Substitution of this expression into Equation 3.5.3 allows the time delay compensation part of the Smith predictor to be written as

$$D_2(z) = \frac{K_p[(1 - f_1)z^{-1} - (c_1 + c_2 z^{-1})z^{N-1}]}{(1 - f_1 z^{-1})} \qquad (3.5.4)$$

where $f_1 = \exp(T/T_p)$
$f_2 = \exp(-m_p T/T_p)$
$c_1 = 1 - f_2$
$c_2 = f_2 - f_1$
$m_p = 1 - T_d/T + P$
$P = T_d/T$
$M = T_m/T$
$N = P + M$

Substitution of Equations 3.5.2 and 3.5.4 into Equation 3.5.1 gives the discrete form of the Smith predictor given in Table 3.5.1.

Table 3.5.1

SMITH PREDICTOR

$$D(z) = \frac{U(z)}{E(z)} = \frac{a_0 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3}}{b_0 + b_1 z^{-1} + b_2 z^{-2} + b_3 z^{-3} + b_{N+1} z^{-N-1} + b_{N+2} z^{-N-2} + b_{N+3} z^{-N-3} + b_{N+4} z^{-N-4}} \quad (3.5.5)$$

$$u(k) = \frac{1}{b_0}\,[a_0 e(k) + a_1 e(k-1) + a_2 e(k-2) + a_3 e(k-3) - b_1 u(k-1) - b_2 u(k-2) - b_3 u(k-3) - b_{N+1} u(k-N-1) - b_{N+2} u(k-N\ 2) - b_{N+3} u(k-N\ 3) - b_{N+4} u(k-N\ 4)] \quad (3.5.6)$$

where $a_0 = a'_0$

$a_1 = a'_1 - f_1 a'_0$

$a_2 = a'_2 - f_1 a'_1$

$a_3 = -f_1 a'_2$

$a_0 = K_C + K_I + K_D$

$a_1 = -(K_I + 2K_D)$

$a_2 = K_D$

$b_0 = 1$

$b_1 = K_p a_0 (1 - f_1) - (1 + f_1)$

$b_2 = K_p a_1 (1 - f_1) + f_1$

$b_3 = K_p a_2 (1 - f_1)$

$b_{N+1} = -K_p a_0 c_1$

$b_{N+2} = -K_p (a_1 c_1 + a_0 c_2)$

$b_{N+3} = -K_p (a_2 c_1 + a_1 c_2)$

$b_{N+4} = K_p a_2 c_2$

$f_1 = \exp(-T/T_p)$

$f_2 = \exp(-m_p T/T_p)$

$$c1 = 1 - f_2$$

$$c_2 = f_2 - f_1$$

$$m_p = 1 - T_d/T + P$$

$$P = T_d/T$$

$$M = T_m/T$$

$$N = P + M$$

3.6 Discrete PID Algorithm

Proportional-integral (PI) and proportional-integral-derivative (PID) control algorithms are the most commonly used control algorithms in industry, however, there are numerous digital equivalent forms of these algorithms. The different forms result basically from different numerical approximations of the integral and derivative terms. Nevertheless, the discrete algorithms can be divided into two main categories, namely the positional form and the incremental form (also known as the velocity form). In this work, the incremental form of the ideal PID algorithm is chosen for the following reasons:

1) it does not require a bias term as in the positional form;
2) it allows for "bumpless" transfer from manual to automatic control;
3) it provides for anti-reset windup; and
4) it is of the form of Equation 3.1.1.

The continuous ideal PID algorithm can be written as

$$u(t) = K_C[e(t) + \frac{1}{T_I} \int e(t)\, dt + T_D \frac{de}{dt}] + u_{ss} \quad (3.6.1)$$

where u_{ss} = steady state output or bias

The digital equivalent of the above equation, obtained by using the rectangular integration technique, is the common positional form of the ideal PID algorithm which can be expressed as:

$$u(k) = K_C e(k) + K_I \sum_{j=0}^{j=k-1} e(k-j) + K_D[e(k) - e(k-1)] + u_{ss} \quad (3.6.2)$$

where $K_I = K_C(T/T_I)$; $K_D = K_C(T_D/T)$

The incremental form of the ideal PID algorithm results by taking the difference between the positional form of the algorithm at the kth sample instant (cf Equation 3.6.2) and the positional form for the (k-1)th sample instant. The incremental form of the ideal PID is then expressed as:

$$u(k) - u(k-1) = (K_C + K_I + K_D)e(k) + (-K_C - 2K_I)e(k-1) + K_D e(k-2) \quad (3.6.3)$$

In the z-domain, the incremental form of the ideal PID algorithm is

$$\frac{U(z)}{E(z)} = \frac{a_0 + a_1 z^{-1} + a_2 z^{-2}}{1 - z^{-1}} \quad (3.6.4)$$

where $a_0 = K_C + K_I + K_D$

$a_1 = -(K_C + 2K_I)$

$a2 = K_D$

4. Distillation Column Models

4.1 Introduction

Both linear and nonlinear models have been developed to described the behaviour of the pilot scale distillation column used for the experimental phase of this work. Linear models have been used primarily in conjunction with the design of digital control algorithms while nonlinear models have been used to simulate the behaviour of the actual distillation column for evaluating the performance of different digital algorithms. In the next section, Section 4.2, the development of the nonlinear model of the binary distillation column used in this work is presented. In Section 4.3, selection of linear models for control studies is discussed. Evaluation of distillation column models and the discussion of simulation results are presented in Sections 4.4 and 4.5 respectively.

4.2 Nonlinear Model

The dynamic model of the binary distillation column used in this work was based on both the material and energy balance equations. Program development was directed to

1) improving agreement between the simulated response and the experimental results;
2) achieving flexibility of adapting different control schemes; and

3) improving efficiency in computational accuracy and speed.

The original version of the nonlinear distillation column model used in this study was developed by Simonsmeier (50), and subsequently modified by Bilec (4). In this work, modifications to improve the computational accuracy and speed were introduced by both the author and his colleague Mr. Lieuson in 1978. Further modifications to enhance the program's flexibility for studying the control behaviour of different control schemes and improve the agreement with experimental results were completed in 1980.

4.2.1 Model Development

The nonlinear binary distillation column model is based on the assumptions of

1) perfect mixing in each stage;
2) mass transfer and heat transfer equilibrium achieved instantaneously;
3) negligible vapour mass holdup; and
4) constant liquid mass holdup.

From a macroscopic point of view, any physical system can be described by material and energy balance equations. This means that the basic balance equation

$$\text{Input} + \text{Generation} = \text{Output} + \text{Accumulation} \tag{4.2.1}$$

must be satisfied at all times. Based on the aforementioned assumptions, the following sets of general equations describe the behaviour of any binary distillation column

Total Mass Balance

$$L_{n+1} - L_n - V_n + V_{n+1} - S_n - F_n = 0 \qquad (4.2.2)$$

Component Balance (on the more volatile component)

$$WT_n \frac{dx_n}{dt} = L_{n+1}x_{n+1} - L_nx_n - V_ny_n + V_{n-1}y_{n-1} - S_nx_n + F_nx_f \qquad (4.2\ 3)$$

Energy Balance (on the more volatile component)

$$WT_n \frac{dh_n}{dt} = L_{n+1}h_{n+1} - L_nh_n - V_nH_n + V_{n-1}H_{n-1} - S_nh_n + F_nh_f - Q_{Ln} + Q_{In} \qquad (4.2.4)$$

where n = stage number

L = liquid mass flow rate

V = vapour mass flow rate

S = side stream mass flow rate

F = feed mass flow rate

f = associated with feed

WT = liquid mass holdup

x = liquid composition

y = vapour composition

h = liquid enthalpy

H = vapour enthalpy

Q_L = heat loss

Q_I = heat input

A tray described by these equations is shown in Figure 4.2.1. The following functional relations are also employed to simplify the problem formulation of the binary distillation column model

$$H_n = H(y_n) \qquad (4.2.5)$$

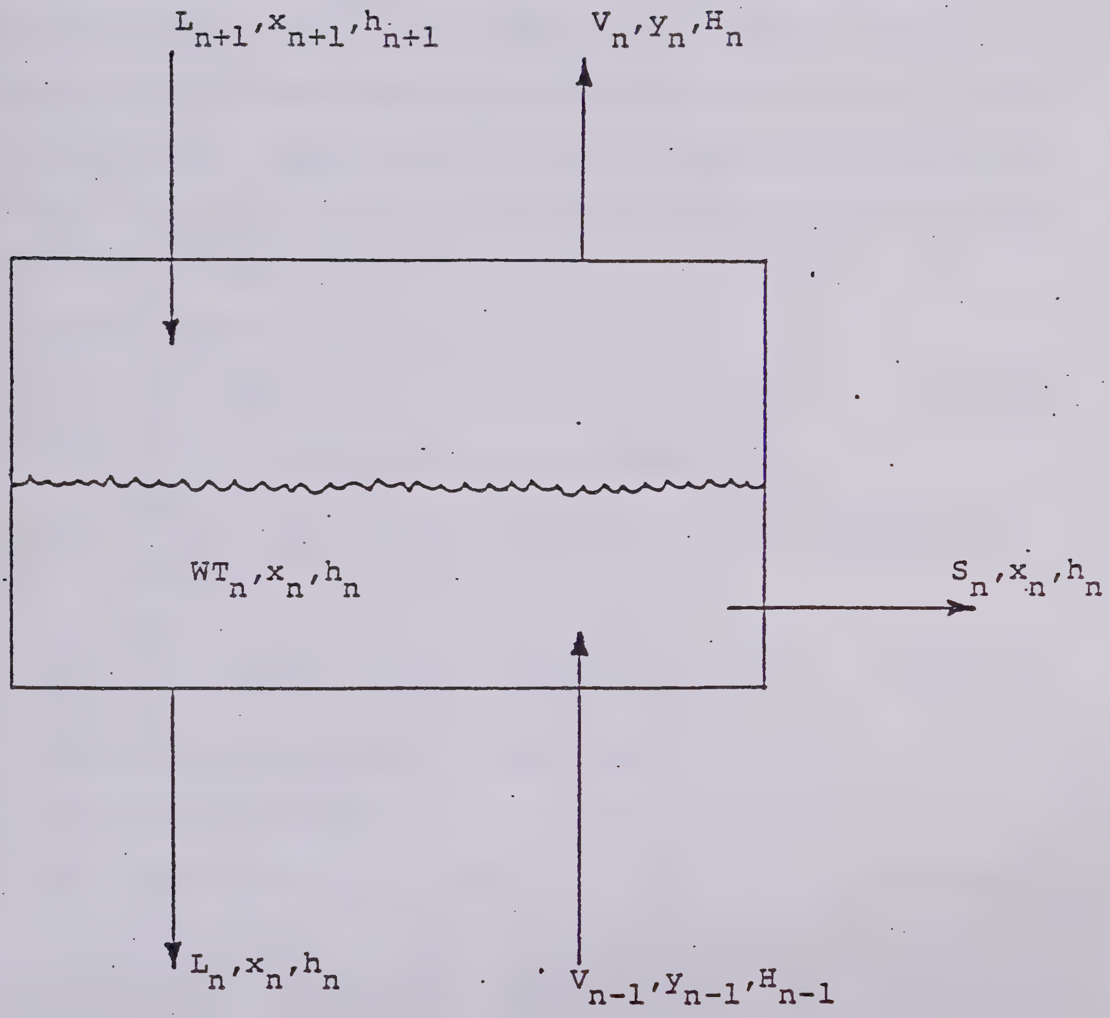

$L_{n+1}, x_{n+1}, h_{n+1}$
V_n, Y_n, H_n
WT_n, x_n, h_n
S_n, x_n, h_n
L_n, x_n, h_n
$V_{n-1}, Y_{n-1}, H_{n-1}$

Figure 4.2.1 Schematic Diagram of an Equilibrium Stage

$$h_n = h(x_n) \qquad (4.2.6)$$

$$y_n^* = y(x_n) \qquad (4.2.7)$$

$$y_n = y_{n-1}^* + E_n(y_n^* - y_{n-1}) \qquad (4.2.8)$$

where y^* = equilibrium vapour composition

E = Murphree vapour efficiency

For the pilot scale distillation column in the Department of Chemical Engineering at the University of Alberta, there is no side stream drawoff and the only feed to the column is at the fifth stage (fourth tray), so it follows from Equations 4.2.2 to 4.4.4 that the equations for the nonlinear binary distillation column are

At the reboiler

$$L_2 - L_1 - V_1 = 0 \qquad (4.2.9)$$

note: L_1 is the bottom product flow.

$$WT_1 \frac{dx_1}{dt} = L_2x_2 - L_1x_1 - V_1y_1 \qquad (4.2.10)$$

$$WT_1 \frac{dh_1}{dt} = L_2h_2 - L_1h_1 - V_1H_1 - Q_{L1} + Q_R \qquad (4.2.11)$$

where Q_R is the reboiler heat duty

At the feed stage

$$L_6 - L_5 - V_5 + V_4 + F = 0 \qquad (4.2.12)$$

$$WT_5 \frac{dx_5}{dt} = L_6x_6 - L_5x_5 - V_5y_5 + V_4y_4 + Fx_F \qquad (4.2.13)$$

$$WT_5 \frac{dh_5}{dt} = L_6h_6 - L_5h_5 - V_5H_5 + V_4H_4 + Fh_F - Q_{L5} \qquad (4.2.14)$$

At the condenser

$$V_9 - L_{10} - Re = 0 \tag{4.2.15}$$

note: L_{10} is the top product flow.

$$WT_{10} \frac{dx_{10}}{dt} = V_9 y_9 - L_{10} x_{10} - Re x_{10} \tag{4.2.16}$$

$$WT_{10} \frac{dh_{10}}{dt} = V_9 H_9 - L_{10} h_{10} - Re h_{10} - Q_{L10} - Q_{cooling} \tag{4.2.17}$$

For stages n = 2 3,4,6,7,8,9

$$L_{n+1} - L_n - V_n + V_{n-1} = 0 \tag{4.2.18}$$

$$WT_n \frac{dx_n}{dt} = L_{n+1} x_{n+1} - L_n x_n - V_n y_n + V_{n-1} y_{n-1} \tag{4.2.19}$$

$$WT_n \frac{dh_n}{dt} = L_{n+1} h_{n+1} - L_n h_n - V_n H_n + V_{n-1} H_{n-1} \tag{4 2.20}$$

Note: for n = 9, h_{Re}, the reflux enthalpy rather than h_{10}, the liquid enthalpy in the condenser is used.

There are total of 30 equations available to describe the distillation columns dynamics, however, there are only 29 basic unknowns, namely 10 liquid compositions, 10 liquid flow rates, and 9 vapour flow rates. Since the reflux flow rate is the manipulated variable for top composition control and reflux enthalpy is maintained slightly lower than the liquid enthalpy of the 9th stage to prevent flashing when the reflux flow is return to the column at the 9th stage, Equation 4.2.17 does not need to be utilized directly in the development of the nonlinear distillation column model.

4.2.2 Problem Formulation

There are two approaches, namely the substitution method and the matrix inversion method, to solve the aforementioned system of equations. Previous work by Simonsmeier (50) has demonstrated that the matrix inversion method is more efficient than the substitution method, therefore, only the matrix inversion method will be discussed in this subsection.

In the matrix inversion method, the system of equations for the distillation column is formulated into the following matrix expressions.

$$\underline{\underline{A}} \begin{bmatrix} \underline{L} \\ \\ \underline{V} \end{bmatrix} = \begin{bmatrix} \underline{FT1} \\ \\ \underline{FT2} \end{bmatrix} \qquad (4.2.21)$$

$$\dot{\underline{x}} = \underline{\underline{B}}\ \underline{x} \qquad (4.2.22)$$

The detailed structure of Equations 4.2.21 and 4.2.22 is shown in Tables 4.2.1 and 4.2.2 respectively. From Equation 4.2.21, it follows that:

$$\begin{bmatrix} \underline{L} \\ \\ \underline{V} \end{bmatrix} = \underline{\underline{A}}^{-1} \begin{bmatrix} \underline{FT1} \\ \\ \underline{FT2} \end{bmatrix} \qquad (4.2.23)$$

In Equation 4.2.22, $\underline{x}$ can be approximated by the backward difference method.

$$\dot{\underline{x}} = \frac{\underline{x}^{k} - \underline{x}^{k-1}}{\Delta t} \qquad (4.2.24)$$

where k designates the kth integration step

However, the right hand side of the above equation is a better approximation of $\underline{x}_{avg}$ than $\underline{x}$ (50), thus,

Table 4.2.1

Structure of Equation 4.2.1

$$
\left[\begin{array}{ccccccccccccccccccc}
-1 & 1 & & & & & & & & & -1 & & & & & & & & \\
& -1 & 1 & & & & & & & & 1 & -1 & & & & & & & \\
& & -1 & 1 & & & & & & & & 1 & -1 & & & & & & \\
& & & -1 & 1 & & & & & & & & 1 & -1 & & & & & \\
& & & & -1 & 1 & & & & & & & & 1 & -1 & & & & \\
& & & & & -1 & 1 & & & & & & & & 1 & -1 & & & \\
& & & & & & -1 & 1 & & & & & & & & 1 & -1 & & \\
& & & & & & & -1 & 1 & & & & & & & & 1 & -1 & \\
& & & & & & & & -1 & 1 & & & & & & & & 1 & -1 \\
& & & & & & & & & -1 & & & & & & & & & 1 \\
a_1 & b_1 & & & & & & & & & -1 & & & & & & & & \\
& a_2 & b_2 & & & & & & & & c_2 & -1 & & & & & & & \\
& & a_3 & b_3 & & & & & & & & c_3 & -1 & & & & & & \\
& & & a_4 & b_4 & & & & & & & & c_4 & -1 & & & & & \\
& & & & a_5 & b_5 & & & & & & & & c_5 & -1 & & & & \\
& & & & & a_6 & b_6 & & & & & & & & c_6 & -1 & & & \\
& & & & & & a_7 & b_7 & & & & & & & & c_7 & -1 & & \\
& & & & & & & a_8 & b_8 & & & & & & & & c_8 & -1 & \\
& & & & & & & & a_9 & b_9 & & & & & & & & c_9 & -1
\end{array}\right]
\left[\begin{array}{c}
L_1 \\ L_2 \\ L_3 \\ L_4 \\ L_5 \\ L_6 \\ L_7 \\ L_8 \\ L_9 \\ L_{10} \\ V_1 \\ V_2 \\ V_3 \\ V_4 \\ V_5 \\ V_6 \\ V_7 \\ V_8 \\ V_9
\end{array}\right]
=
\left[\begin{array}{c}
0 \\ 0 \\ 0 \\ 0 \\ -F \\ 0 \\ 0 \\ 0 \\ 0 \\ D \\ d_1 \\ d_2 \\ d_3 \\ d_4 \\ d_5 \\ d_6 \\ d_7 \\ d_8 \\ d_9
\end{array}\right]
$$

where $a_i = -h_i / H_i$ $\quad i = 1, 2, 3, \ldots 8, 9$

$b_i = h_{i+1} / H_i$ $\quad i = 1, 2, 3, \ldots 8, 9$

$c_i = H_{i-1} / H_i$ $\quad i = 2, 3, 4, \ldots 8, 9$

$$d_1 = \left(WT_1 \frac{dh_1}{dt} + Q_{L1} + Q_R\right) / H_1$$

$$d_i = \left(WT_i \frac{dh_i}{dt} + Q_{Li}\right) / H_i \qquad i = 2, 3, 4, \ldots 8, 9$$

Table 4.2.2

Structure of Equation 4.2.2

$$\begin{array}{cccc} \underline{\dot{X}} & & \underline{\underline{B}} & \underline{X} \\ \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \\ \dot{x}_5 \\ \dot{x}_6 \\ \dot{x}_7 \\ \dot{x}_8 \\ \dot{x}_9 \\ \dot{x}_{10} \end{bmatrix} & = & \begin{bmatrix} a_1 & c_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_2 & a_2 & c_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & b_3 & a_3 & c_3 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & b_4 & a_4 & c_4 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & b_5 & a_5 & c_5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & b_6 & a_6 & c_6 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & b_7 & a_7 & c_7 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & b_8 & a_8 & c_8 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & b_9 & a_9 & c_9 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & b_{10} & a_{10} \end{bmatrix} & \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \\ x_9 \\ x_{10} \end{bmatrix} \end{array}$$

where

$$a_n = \frac{1}{WT_n} [V_n (1 - K_n) - L_{n+1} - V_{n-1}]$$

$n = 2,3,4,6,7,8,9,10$

$$a_5 = \frac{1}{WT5} [V_5 (1 - K_5) - L_6 - V_4 + F (R - 1)]$$

$$b_n = \frac{1}{WT_n} V_{n-1} K_{n-1} \qquad n = 2,3\ 4,5,6,7,8,9,10$$

$$c_n = \frac{1}{WT_n} L_{n+1} \qquad n = 1,2,3,4,5,6,7,8,9$$

$K_n = y_n / x_n$

$R = x_F / x_5$

$$\frac{\underline{x}^{k} - \underline{x}^{k-1}}{\Delta t} = \underline{x}_{avg} = 0.50(\underline{\dot{x}}^{k} + \underline{\dot{x}}^{k-1})$$

$$= 0.50(\underline{\underline{B}}^{k}\underline{x}^{k} + \underline{\underline{B}}^{k-1}\underline{x}^{k-1}) \qquad (4.2.25)$$

If the integration interval is several orders of magnitude smaller than the mean time constant of the process, the following expression will be valid.

$$\underline{\underline{B}}^{k} \sim \underline{\underline{B}}^{k-1} \qquad (4.2.26)$$

Therefore,

$$\frac{\underline{x}^{k} - \underline{x}^{k-1}}{\Delta t} = 0.5(\underline{\underline{B}}^{k-1}\underline{x}^{k} + \underline{\underline{B}}^{k-1}\underline{x}^{k-1}) \qquad (4.2.27)$$

or

$$\underline{x}^{k} = (\underline{\underline{I}} - 0.5\Delta t\underline{\underline{B}}^{k-1})^{-1}(\underline{\underline{I}} + 0.5\Delta t\underline{\underline{B}}^{k-1})\underline{x}^{k-1} \qquad (4.2.28)$$

4.2.3 Numerical Solution

There are numerous computer library subroutines for solving system of equations using direct matrix inversion, however, these subroutines are intended for general matrices. For matrices with a large number of zero elements, such as the tridiagonal matrices, direct matrix inversion is not necessary. For inverting tridiagonal matrices, the Thomas algorithm (24) is the most effective and efficient approach and it is chosen for solving the liquid compositions in the model. For matrices which have a large number of zero elements but do not have the structure of a tridiagonal matrix, an iterative approach could be more efficient than direct inversion method if the matrices are stable and good initial guesses are available. The iterative method is particularly

suitable for distillation modelling, because the distillation column is a slow process, thus the information from the previous integration cycle will be a good initial guess for the present integration cycle, if the integration interval is small enough. Among iterative methods, the Gauss-Seidel method is very effective so it is chosen for solving for the liquid and vapour flow rates in the model.

Using the Thomas algorithm to solve for the liquid compositions and the Gauss-Seidel method to solve for the liquid and vapour flow rates, the computational efficiency has been improved drastically while the accuracy of the simulated results remains the same or even better. For the solution procedure employed by Bilec (4), the amount of CPU time required by the Amdahl 470/V7 computer for a typical open loop simulation (total of 360 integration steps) was more than 9 seconds while the new solution scheme used in this work requires less than 3 seconds of CPU time for the same simulated time period. The FORTRAN program listing of the new model and the associated subroutines are available from the DACS Centre.

4.3 Linear Model

Nonlinear models are very useful for simulation studies of physical systems, however, to use nonlinear models, such as the nonlinear binary distillation column model, in control algorithm design is inappropriate simply because mathematical manipulation is almost impossible. Linear models or

transfer function models, on the other hand, are favoured by control engineers for their mathematical simplicity as well as for the ease of determination of model parameters.

The most commonly used transfer function models in classical control system design are in the Laplace domain, because they represent continuous systems. Most industrial processes can be represented by first order plus time delay models or second order plus time delay models. Higher order models, are seldom used because the parameters in these models are difficult to identify by simple procedures. In this work, only first order plus time delay models are considered because they simplify the development of digital control algorithms.

4.4 Evaluation of Distillation Column Models

The use of nonlinear model simulation is to provide control engineers with a more realistic evaluation of the performance of the control algorithm prior to the actual implementation, therefore the simulated open loop responses should match closely with the actual experimental data. Three sets of open loop tests were conducted on the pilot scale distillation column for verifying the nonlinear model. The tests were performed for ±25% step disturbances in feed flow rate, ±10% step disturbances in reflux flow and ±8% step disturbances in steam flow rate. In order to match the simulated open loop responses with the experimental results, the following procedure was followed:

1. Obtain all variables of the nonlinear binary distillation column model at the initial steady state conditions:
    a. Feed flow rate, reflux flow rate, and steam flow rate.
    b. Feed composition, top product composition and bottom product composition.
    c. The column temperature profile.
    d. The liquid composition profile.
    e. The liquid mass holdup profile.
    f. The temperature, liquid composition and liquid mass holdup profiles are not critical to the simulation if only the terminal composition responses are of particular interest. However, the availability of actual data for these profiles will ease the verification procedure. In this project, data from Bilec (4) are used as the initial estimate of these profiles.
2. Estimate the initial heat loss profile. One method of estimating this profile is to distribute the total heat loss (obtained from the experimental heat loss) to each stage according to the difference between the stage temperature and the ambient temperature.
3. Estimate the initial tray efficiency profile.

4. Enter the above data into the appropriate location in the data file.
5. Simulate the steady state operation of the distillation column using the above data.
6. If the simulated steady state conditions, i.e. the top and bottom product compositions (since the terminal compositions are of primary interest), do not shown close agreement with the actual experimental results, the heat loss profile is adjusted and Step 5 is repeated.
7. If the steady state conditions are in agreement, then the simulated conditions will be used as the initial conditions for the open loop simulation.
8. Estimate the above profiles for the new steady state conditions.
9. Simulate the open loop response.
10. If the simulated new steady state conditions do not show agreement with the experimental steady state conditions then adjust the heat loss profile for the predicted new steady state conditions and repeat Step 8.
11. If the transient response of the terminal compositions are not consistent with the experimental response then adjust both the initial and final tray efficiency profile and repeat Step 8.

12. The model parameters must continue to be adjusted so that the steady state predictions agree with the experimental data before matching the transient responses.

Since bottom composition control study is the primary concern of this project, the matching of top composition responses is not of concern. The simulated nonlinear model predicted bottom composition responses using the above procedure and the experimental responses are shown in Figures 4.4.1 to 4.4.6. The simulated responses shown reasonable agreement with the actual experimental data except that the nonlinear model predicts faster column dynamics than is observed experimentally when the disturbance is either the steam or feed flow rate.

In order to perform simulation studies using the nonlinear distillation column model, a set of transfer functions that can represent the simulated nonlinear model response are required for control algorithm design. Since the prime objective of this work is the study of the performance of various control algorithms for bottom composition control for the column subjected to a feed flow rate disturbance, the transfer functions of interest are those relating bottom composition and steam flow rate and between bottom composition and feed flow rates. The simulated nonlinear model responses were approximated by first order plus time delay transfer function models. Selection of the transfer function parameters was performed on a trial and error

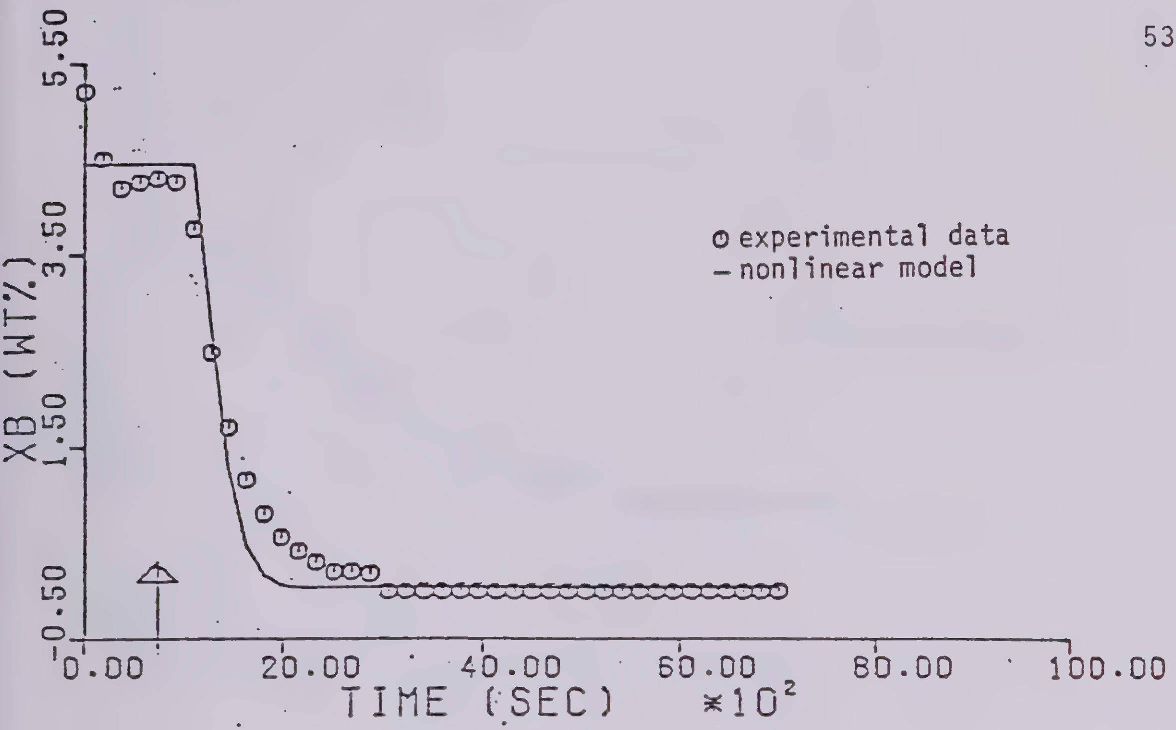


Figure 4.4.1 Comparison of Experimental and Predicted Nonlinear Model Responses of the Bottom Composition for a 25% Step Decrease in Feed Flow Rate

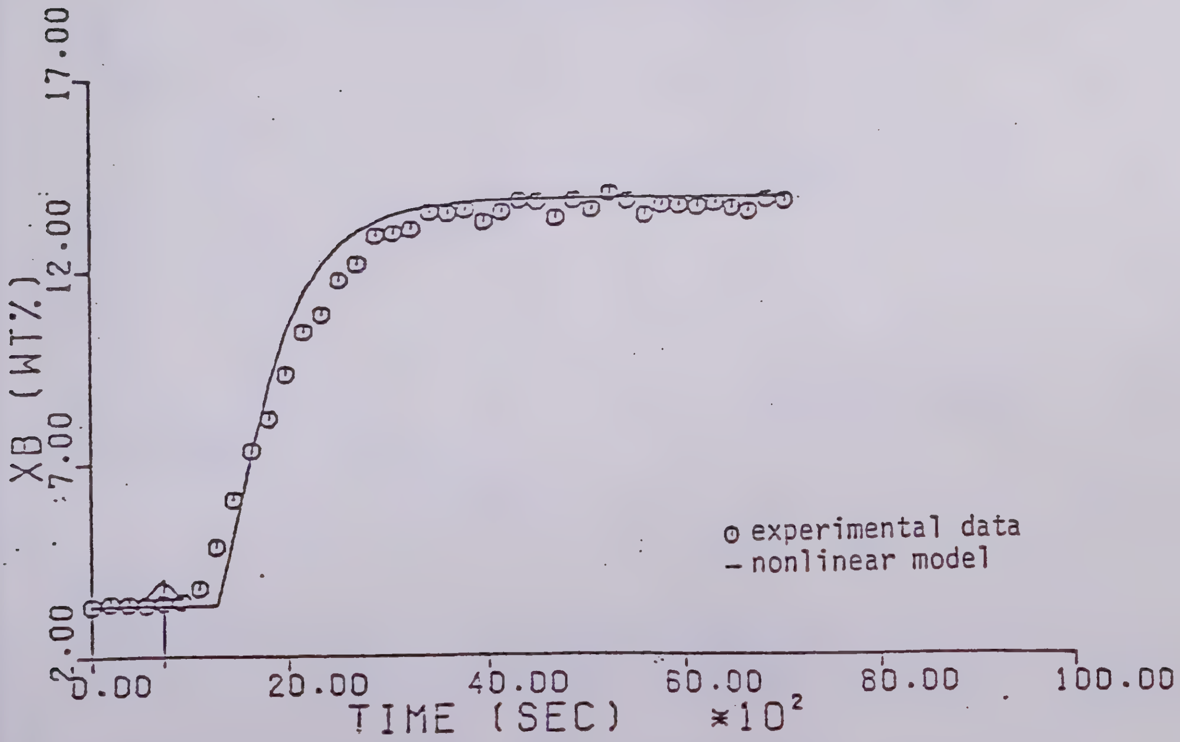


Figure 4.4.2 Comparison of Experimental and Predicted Nonlinear Model Responses of the Bottom Composition for a 25% Step Increase in Feed Flow Rate

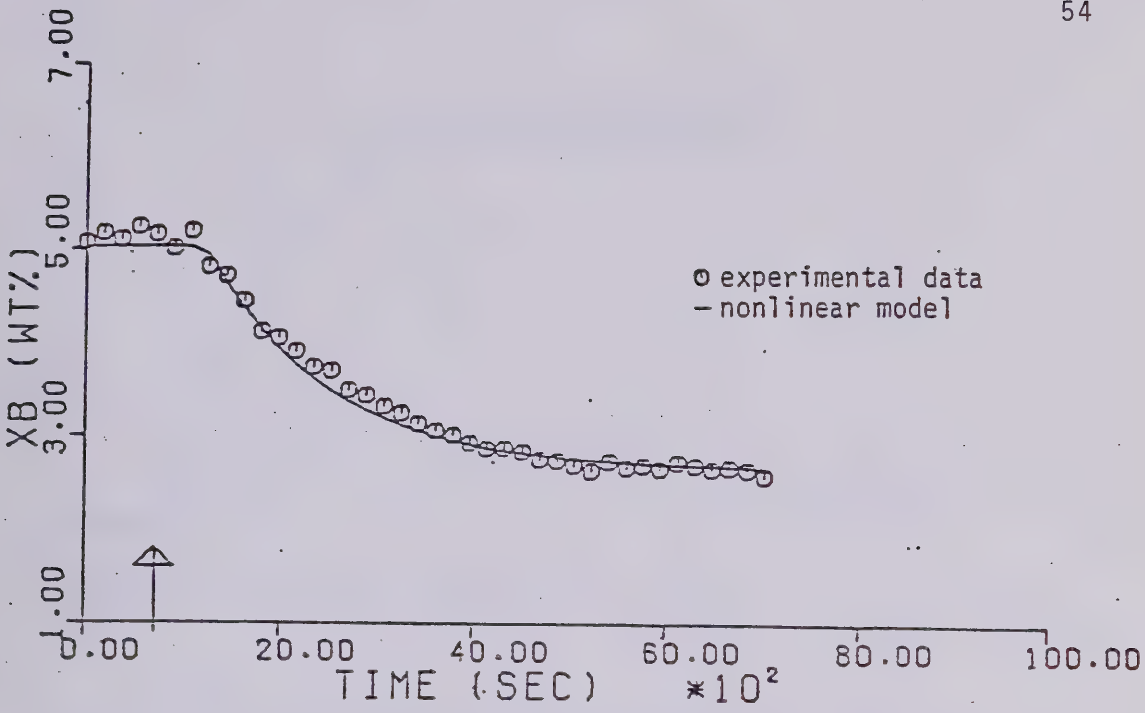


Figure 4.4.3 Comparison of Experimental and Predicted Nonlinear Model Responses of the Bottom Composition for a 10% Step Decrease in Reflux Flow Rate

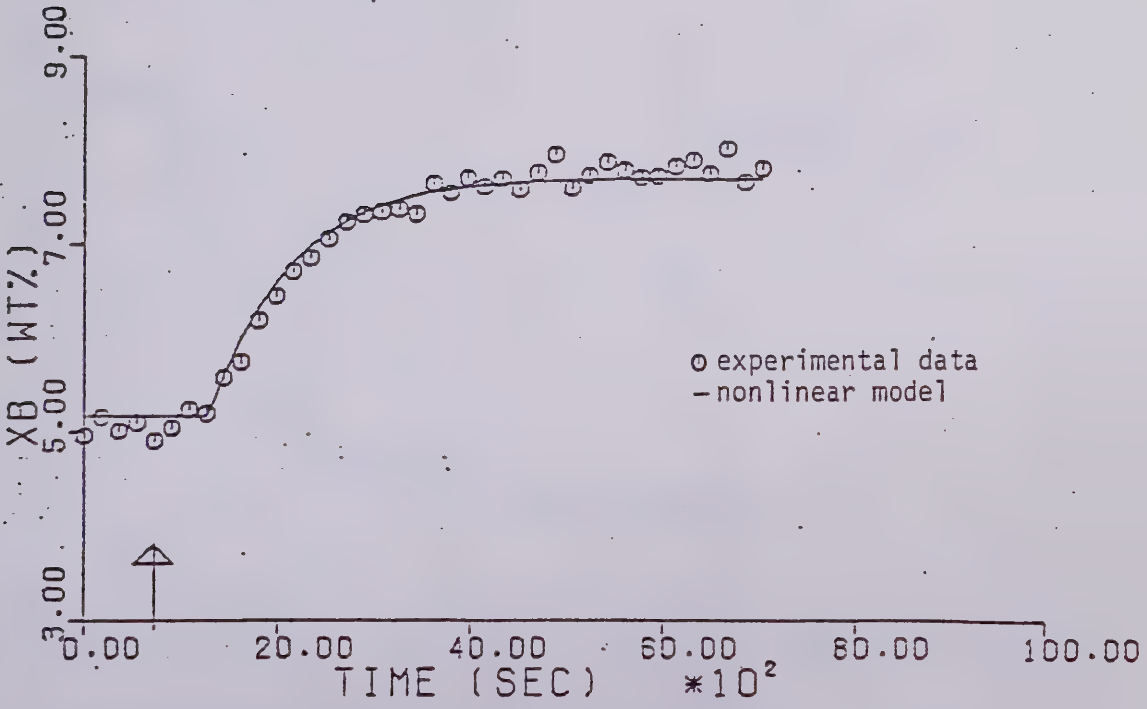


Figure 4.4.4 Comparison of Experimental and Predicted Nonlinear Model Responses of the Bottom Composition for a 10% Step Increase in Reflux Flow Rate

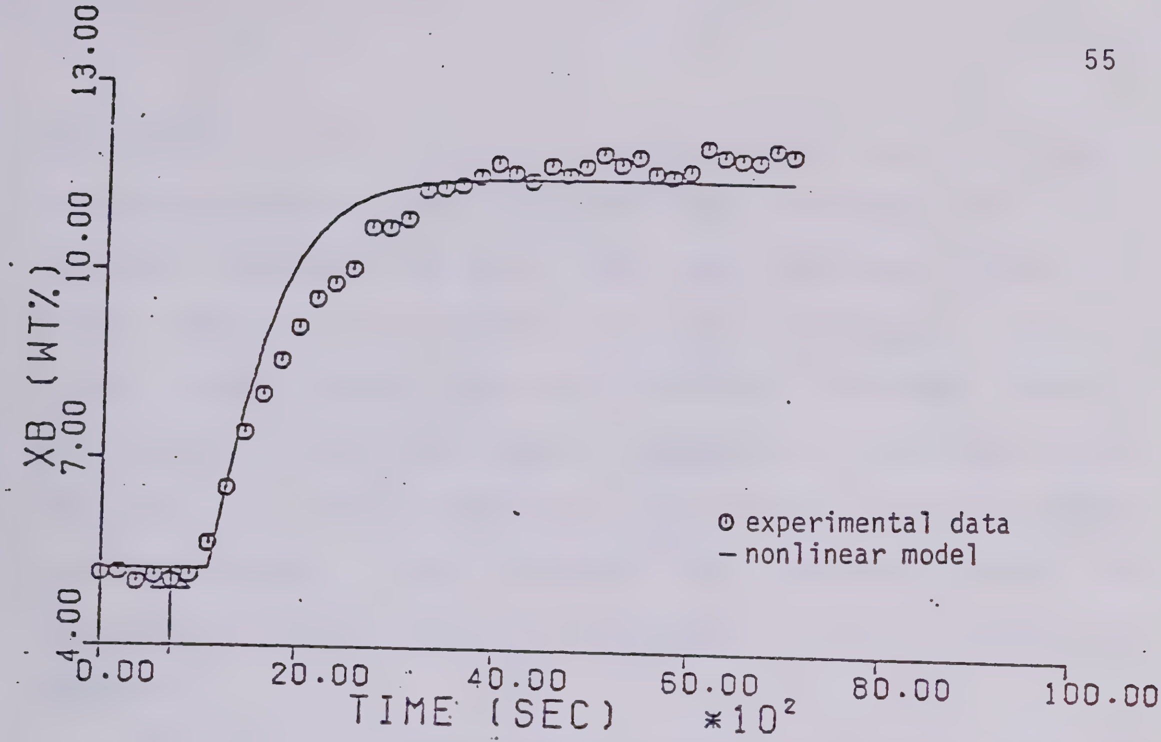


Figure 4.4.5 Comparison of Experimental and Predicted Nonlinear Model Responses of the Bottom Composition for a 8% Step Decrease in Steam Flow Rate

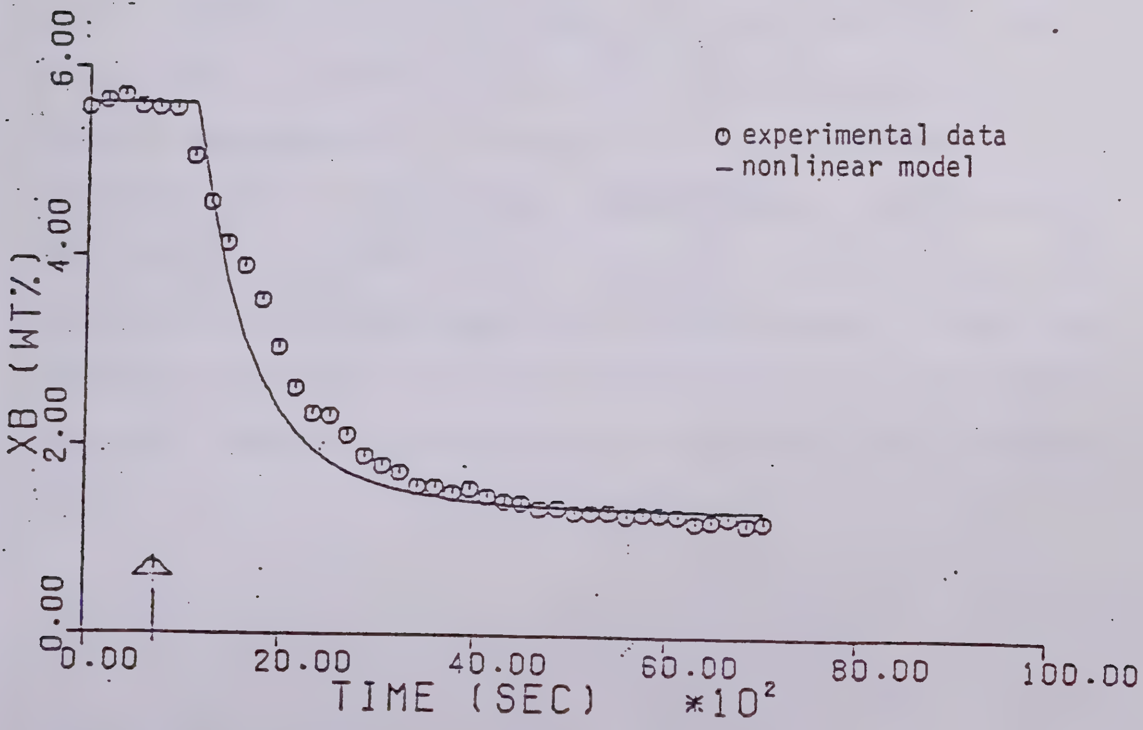


Figure 4.4.6 Comparison of Experimental and Predicted Nonl near Model Responses of the Bottom Composition for a 8% Step Increase in Steam Flow Rate

basis with the aid of a small IBM 360 CSMP simulation program. The transfer function models are listed in Table 4.4.1 and the comparison of the linear and nonlinear simulated bottom composition responses are shown in Figures 4.4.7 to 4.4.10. These figures show that excellent agreement between the linear and nonlinear model simulated bottom composition responses was achieved and the linear models, SLM01 to SLM04 can be assumed to have minimal model parameter error in representing the nonlinear simulated bottom composition response.

Similarly, the experimental open loop results for the ±25% step disturbance in feed flow rate and ±8% step disturbance in steam flow rate were fit by first order plus time delay transfer function models for use with the control algorithms to establish the control law for use in the subsequent experimental evaluation of the performance of the different control algorithms. These transfer function models are listed in Table 4.4.2. Excellent agreement was also achieved between the experimental and simulated linear model responses as shown in Figures 4.4.11 to 4.4.14, hence models ELM01 to ELM04 are assumed to have minimal model parameter error.

Table 4.4.1

Transfer Functions for Simulated Open Loop Responses from Nonlinear Model

Model	Input	X(s)/U(s)	K_p (wt.%/g/s)	T_p (s)	T_d (s)
SLM01	-25% FE	XB(s)/FE(s)	1.00	246	195
SLM02	+25% FE	XB(s)/FE(s)	2.26	577	405
SLM03	-8% ST	XB(s)/ST(s)	-5.24	563	187
SLM04	+8% ST	XB(s)/ST(s)	-4.29	633	187

* - measurement time delay is not included

Table 4.4.2

Transfer Functions for Experimental Open Loop Responses

Model	Input	X(s)/U(s)	K_p (wt.%/g/s)	T_p (s)	T_d (s)
ELM01	-25% FE	XB(s)/FE(s)	1.00	415	195
ELM02	+25% FE	XB(s)/FE(s)	2.26	929	405
ELM03	-8% ST	XB(s)/ST(s)	-5.73	1033	187
ELM04	+8% ST	XB(s)/ST(s)	-4.29	918	187

* - measurement time delay is not included

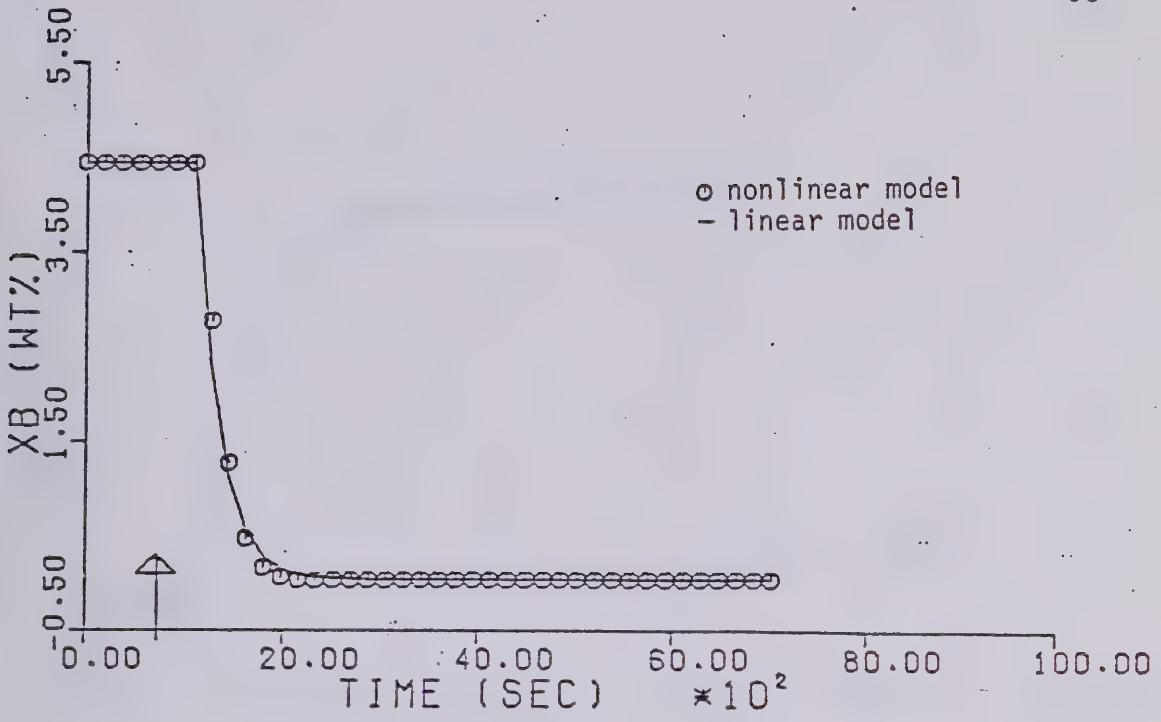


Figure 4.4.7 Comparison of Simulated Nonlinear and Linear Model Predicted Responses of the Bottom Composition for a 25% Step Decrease in Feed Flow Rate

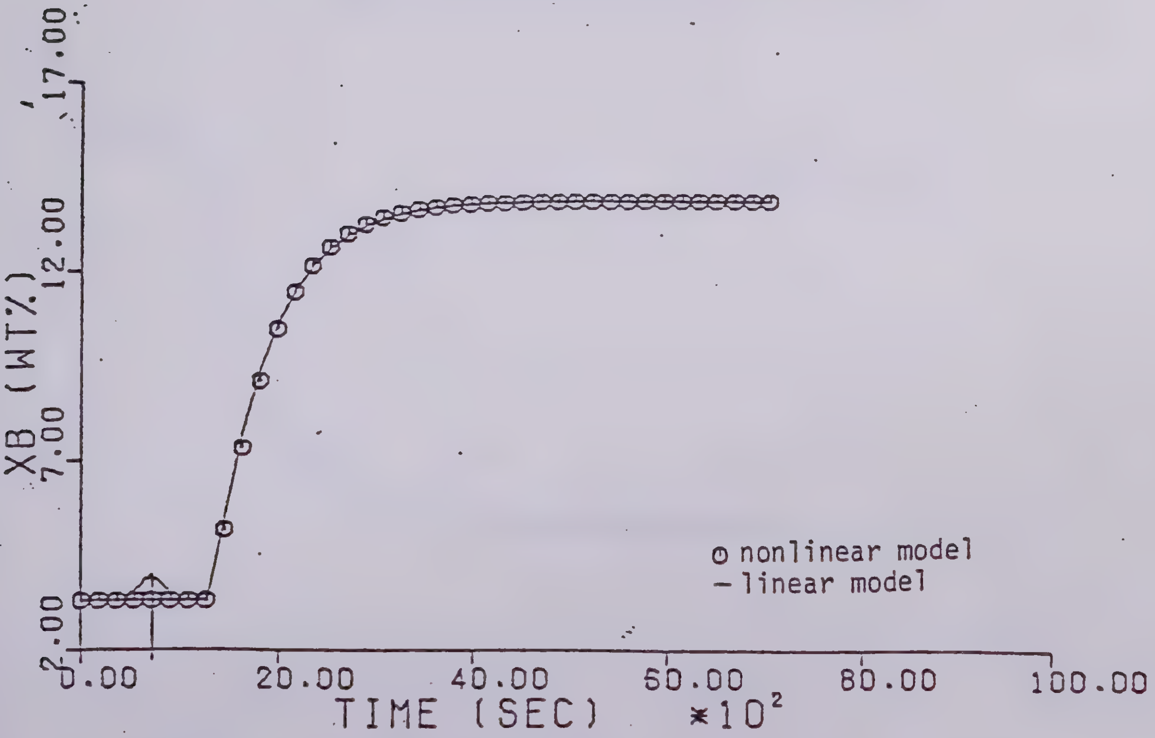


Figure 4.4.8 Comparison of Simulated Nonlinear and Linear Model Predicted Responses of the Bottom Composition for a 25% Step Increase in Feed Flow Rate

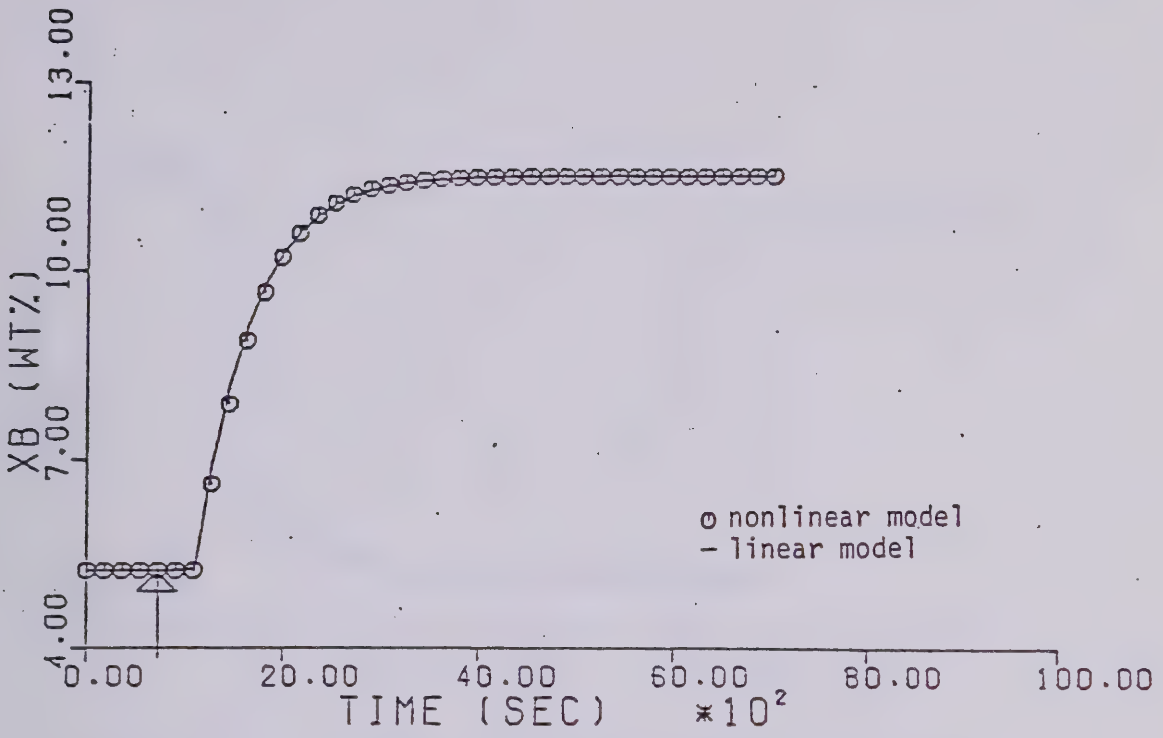


Figure 4.4.9 Comparison of Simulated Nonlinear and Linear Model Predicted Responses of the Bottom Composition for a 8% Step Decrease in Steam Flow Rate

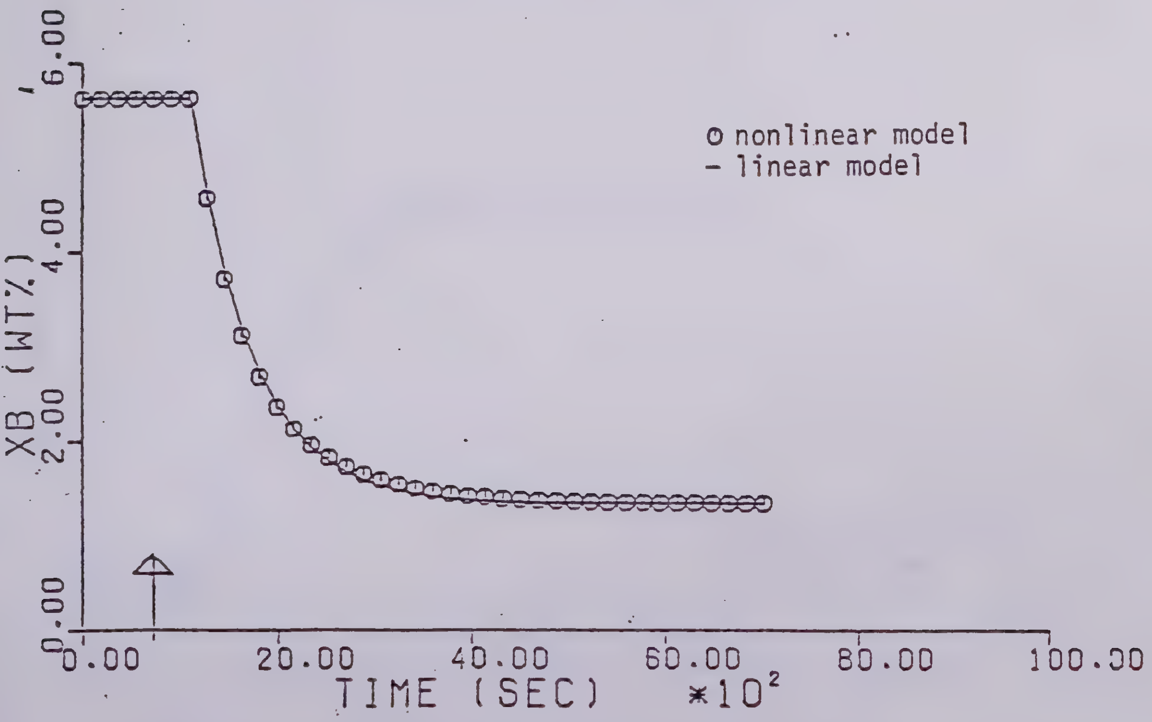


Figure 4.4.10 Comparison of Simulated Nonlinear and Linear Model Predicted Responses of the Bottom Composition for a 8% Step Increase in Steam Flow Rate

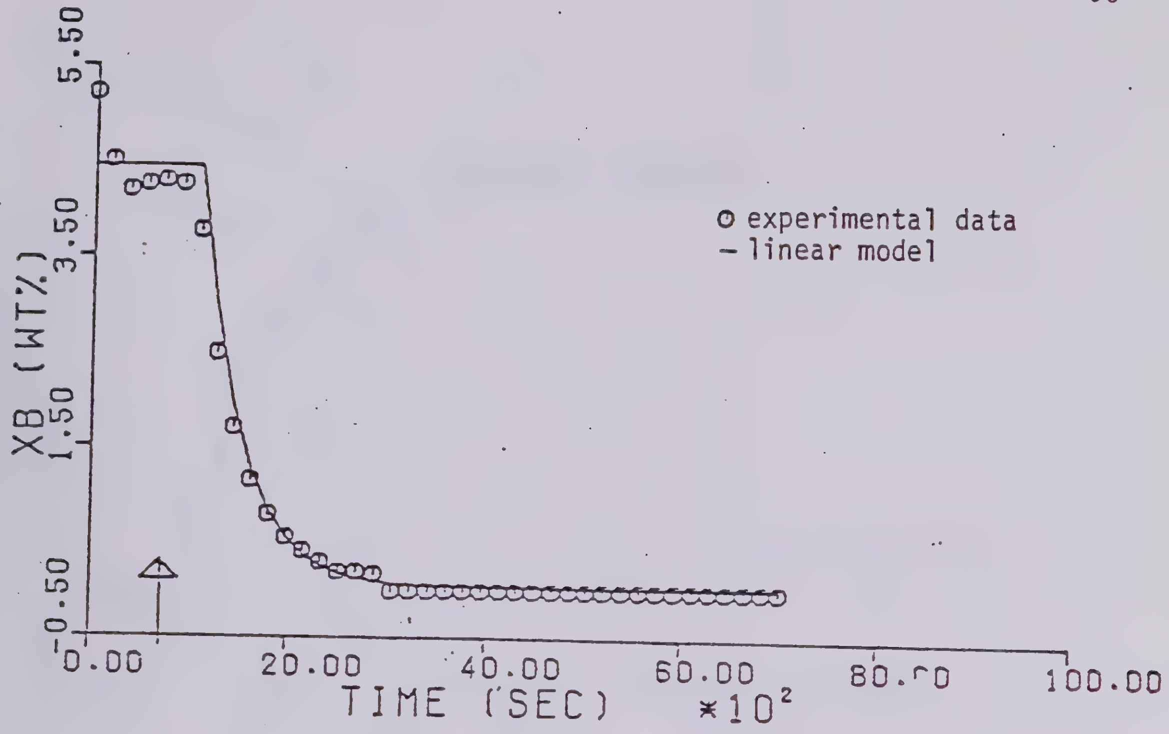


Figure 4.4.11 Comparison of Experimental and Predicted Linear Model Responses of Bottom Composition for a 25% Step Decrease in Feed Flow Rate

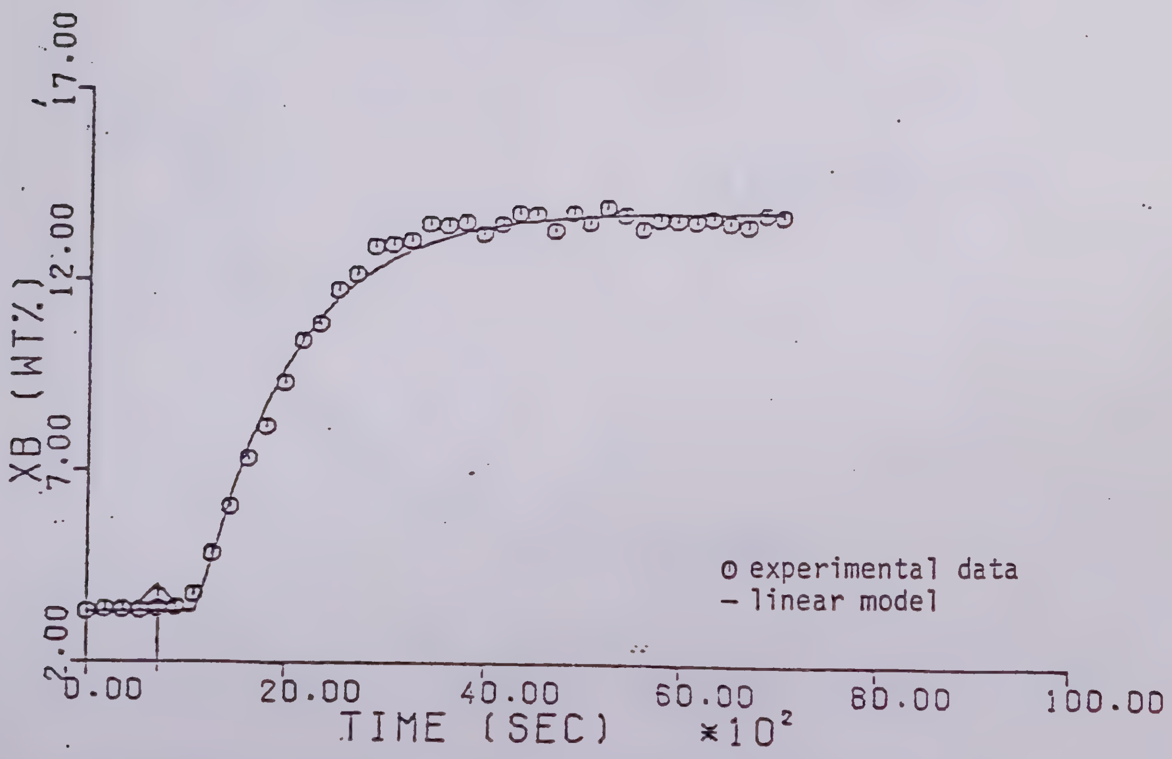


Figure 4.4.12 Comparison of Experimental and Predicted Linear Model Responses of Bottom Composition for a 25% Step Increase in Feed Flow Rate

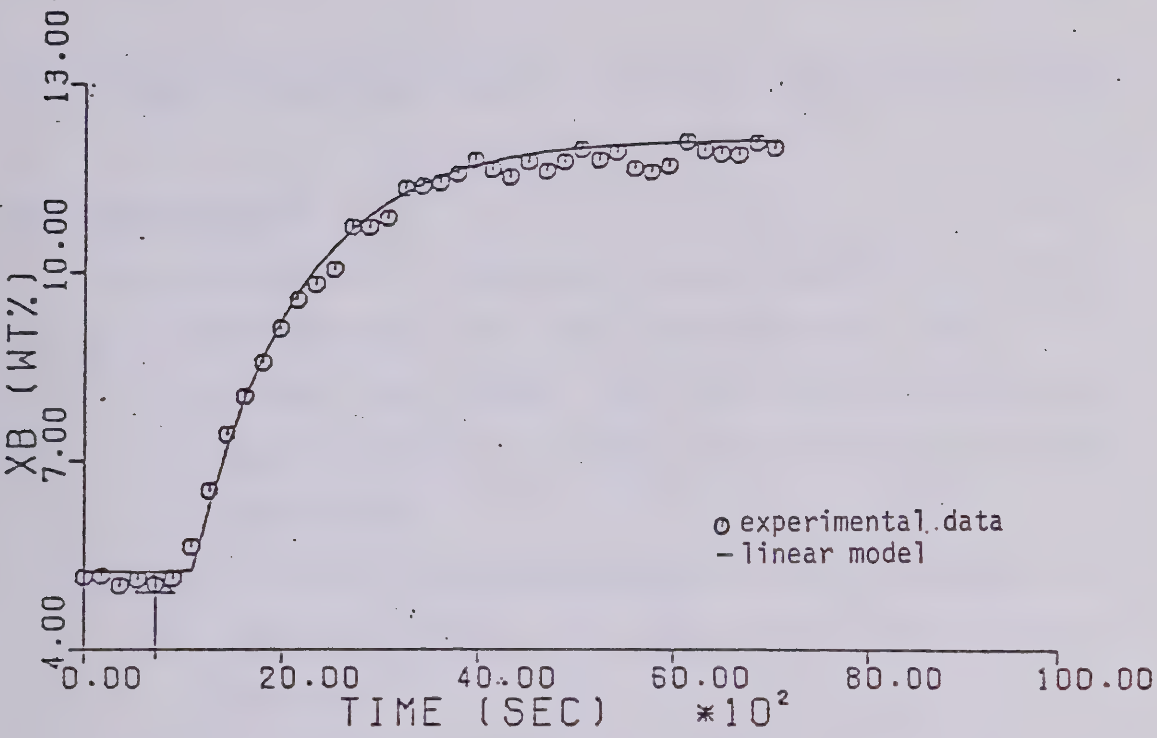


Figure 4.4.13 Comparison of Experimental and Predicted Linear Model Responses of Bottom Composition for a 8% Step Decrease in Steam Flow Rate

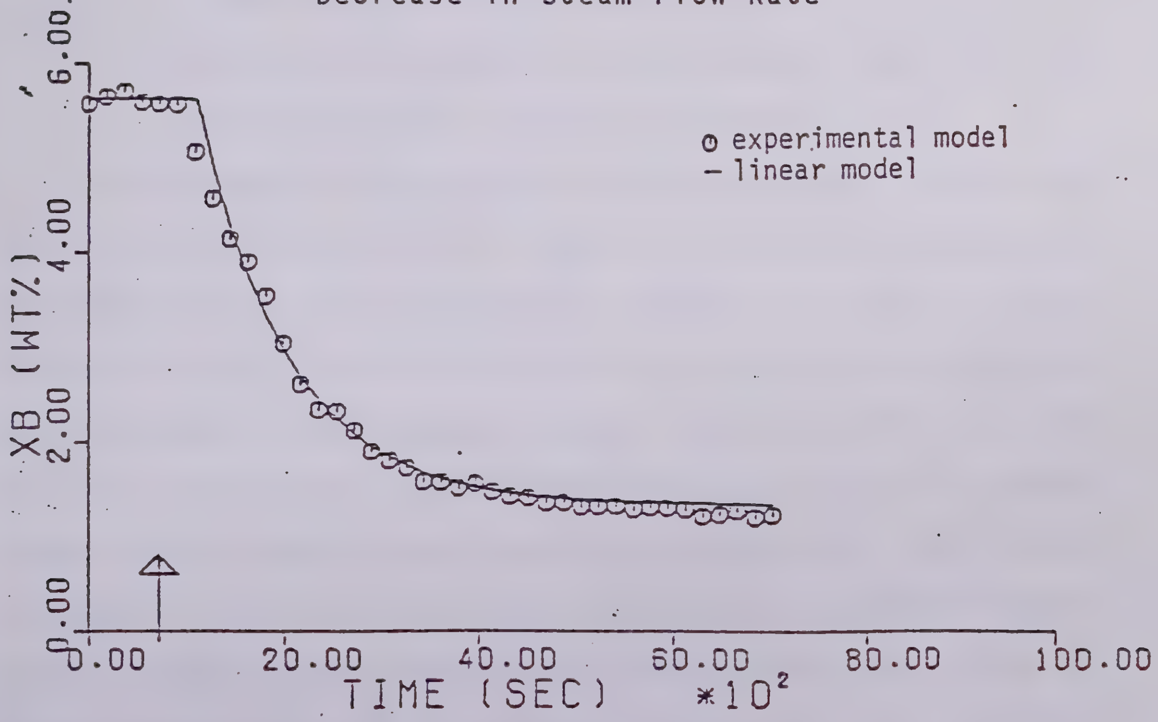


Figure 4.4.14 Comparison of Experimental and Predicted Linear Model Responses of Bottom Composition for a 8% Step Increase in Steam Flow Rate

5. Digital Simulation Studies of Bottom Composition Control

5.1 Introduction

The objectives of studying bottom composition control using on the nonlinear distillation column model are

1) To gain an insight into the control behaviour of the distillation column under different control algorithms.
2) To compare the performance of the different control algorithms under both servo and regulatory control.
3) To gain an insight into the ability of the different control algorithms to compensate for process and measurement time delays.
4) To gain experience on the tuning techniques for the different control algorithms.

The schematic diagram of the distillation column unit to be simulated is shown in Figure 6 2.1 (cf. Chapter 6) and the description of the system is given in Section 6.2 of Chapter 6. The digital simulation of the control system was carried out on the Amdhal 470/V7 computer using the nonlinear distillation model described in Chapter 4. Bottom composition control behaviour was simulated for step changes of ±25% in feed flow rate and ±1% changes in composition set point. The sampling time was 3 minutes consistent with the measurement delay of 3 minutes. Simulations were performed for a total of 165 minutes with the load disturbance or set

point change introduced 15 minutes from the start of the simulation. These conditions were also used in the experimental evaluation, so the simulated results from this section can be compared directly to the results from the experimental evaluation.

5.2 Performance Criteria

In most process control studies, error-integrals are used as the performance criteria for evaluating control algorithms. These measures are used because they characterize the entire time response of the controlled variable when the system is subjected to any disturbance, unlike other criteria, such as the percent overshoot; decay ratio; rise time, response time, etc , which are useful for evaluating the system performance for servo operation. The value of integral of the absolute value of the error (IAE) was used as the criterion for evaluating the performance of the different control algorithms in this work. Although the performance of a control algorithm is judged primarily by the IAE value calculated on the response of the controlled variable, other practical considerations such as the response of the manipulated variable, e.g. valve constraints, maximum rate of change, should not be ignored in actual implementation.

5.3 Performance of the Algorithms for Servo Control

Since the distillation column is a highly nonlinear process, especially the response of the bottom composition

to a change in feed flow rate, it is necessary to use different sets of controller constants for controlling different disturbances. The initial controller settings for the PI and PID algorithms for servo operation were calculated using the correlations suggested by Smith (51) based on either the SLM03 or SLM04 models (cf. Section 4.4). The IAE values for the performance of these control algorithms, after tuning to minimize the IAE value, are summarized in Tables 5.3.1 and 5.3.2. The bottom composition control responses using these algorithms are shown in Figures 5.3.1 to 5.3.4.

For the deadbeat algorithm, the Dahlin algorithm and the Smith predictor, the SLM03 and SLM04 models were used in the design of these algorithms. The IAE values for the performance of these algorithms are summarized in Tables 5.3 1 and 5.3.2. The control performance achieved using these different algorithms is shown by the responses given in Figures 5.3.5 to 5.3.10.

5.4 Performance of the Algorithms for Regulatory Control

For the PI and PID control algorithms, the initial sets of controller constants are, again, calculated using the correlations from Smith (51). The IAE values that resulted using the PI and PID algorithms for regulatory control are listed in Tables 5.4.1 and 5.4.2 while the responses of bottom composition using these two control algorithms are presented in Figures 5.4.1 to 5.4.4. For the deadbeat, Dahlin and Smith predictor algorithms, the initial controller

Table 5.3.1

Summary of Simulated Results for Control of Bottom Composition for a +1% Step Change in Set Point

Algorithm	K_C	K_I	K_D	K_p	T_p	T_d	IAE	Figure
PI	-0.160	-0.039	—	—	—	—	966	5.3.1
PID	-0.198	-0.045	-0.192	—	—	—	758	5.3.3
Deadbeat	—	—	—	-5.24	563	187	721	5.3.5
Dahlin	λ = 14s	—	—	-5.24	563	187	721	5.3.7
Smith Pred.	-0.678	-0.210	—	-5.24	563	187	734	5.3.9

K_C = (g/s)/wt.%

K_p = wt.%/(g/s)

K_I = (g/s)/(wt.%-s)

T_p = s

K_D = (g/s)/(wt.%/s)

T_d = s

IAE = wt.%-s

Table 5.3.2

Summary of Simulated Results for Control of Bottom Composition for a -1% Step Change in Set Point

Algorithm	K_C	K_I	K_D	K_p	T_p	T_d	IAE	Figure
PI	-0.160	-0.039	—	—	—	—	949	5.3.2
PID	-0.240	-0.053	-0.197	—	—	—	740	5.3.4
Deadbeat	—	—	—	-4.29	633	187	672	5.3.6
Dahlin	λ = 20s	—	—	-4.29	633	187	672	5.3.8
Smith Pred.	-0.948	-0.263	—	-4.29	633	187	674	5.3.10

K_C = (g/s)/wt.%

K_p = wt.%/(g/s)

K_I = (g/s)/(wt.%-s)

T_p = s

K_D = (g/s)/(wt.%/s)

T_d = s

IAE = wt.%-s

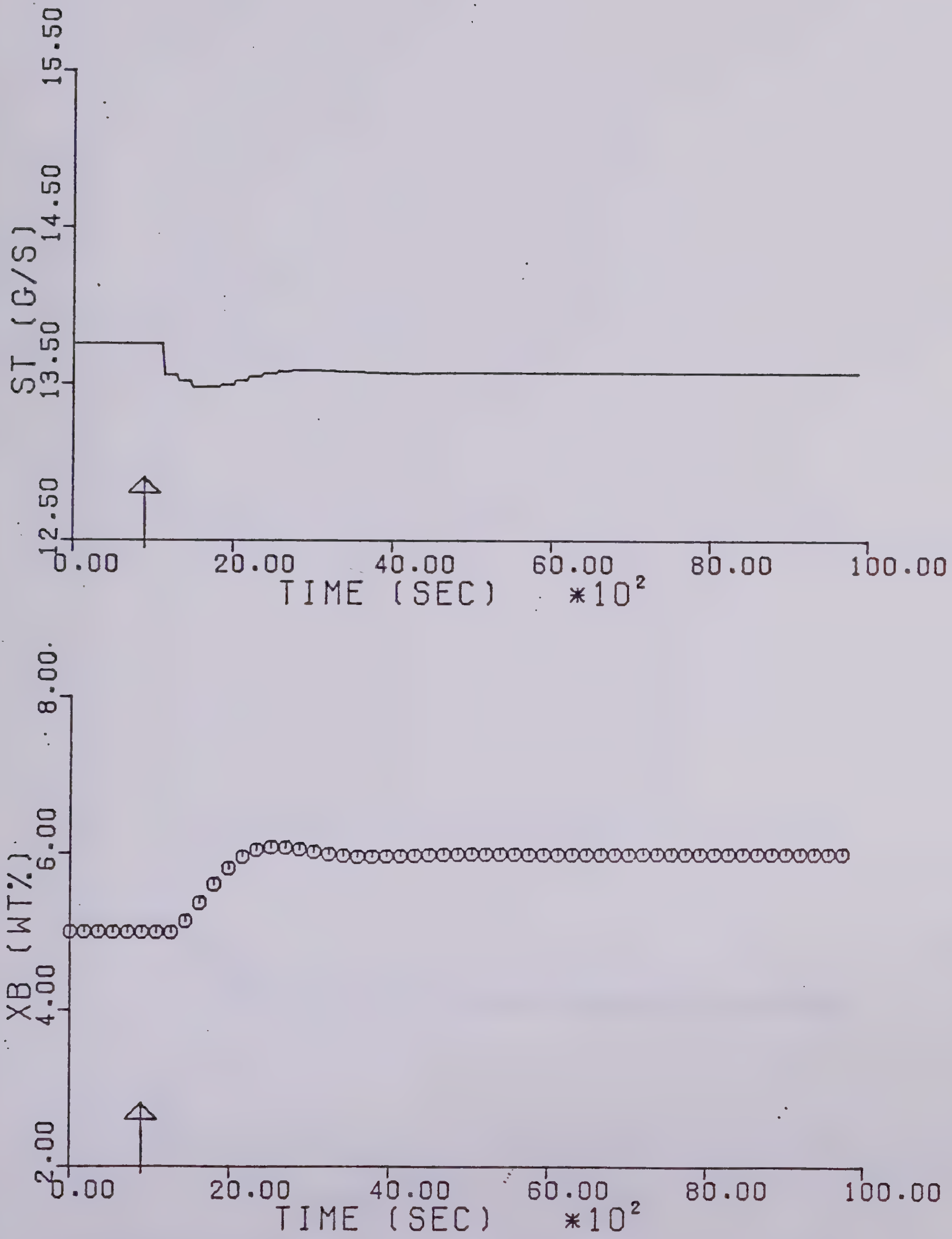


Figure 5.3.1 PI Algorithm Control of Bottom Composition for a +1% Step Change in Set Point (Run S-PI01; $K_C = -0.160$, $K_I = -0.039$)

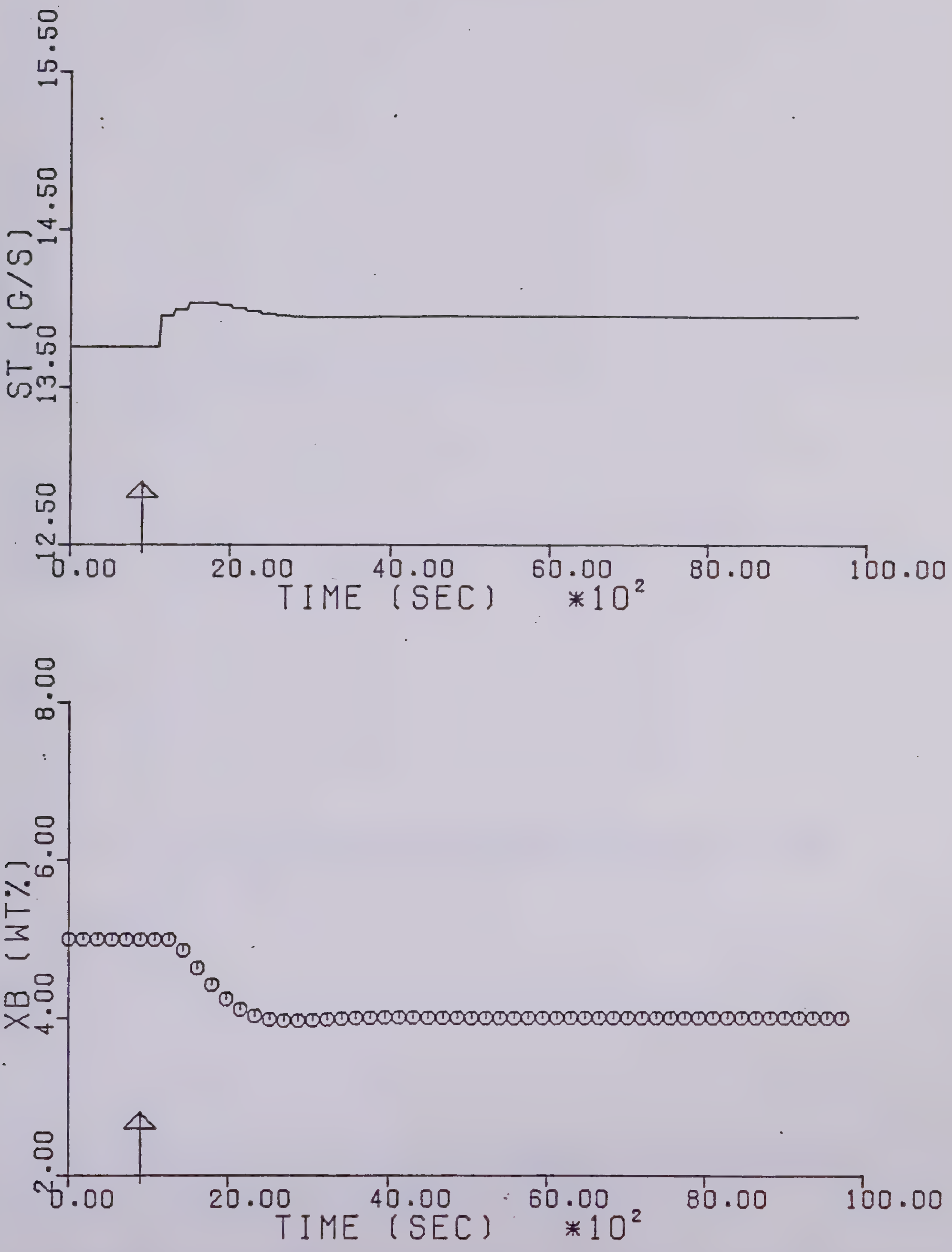


Figure 5.3.2 PI Algorithm Control of Bottom Composition for a -1% Step Change in Set Point (Run S-PI02; K_C = -0.160, K_I = -0.039)

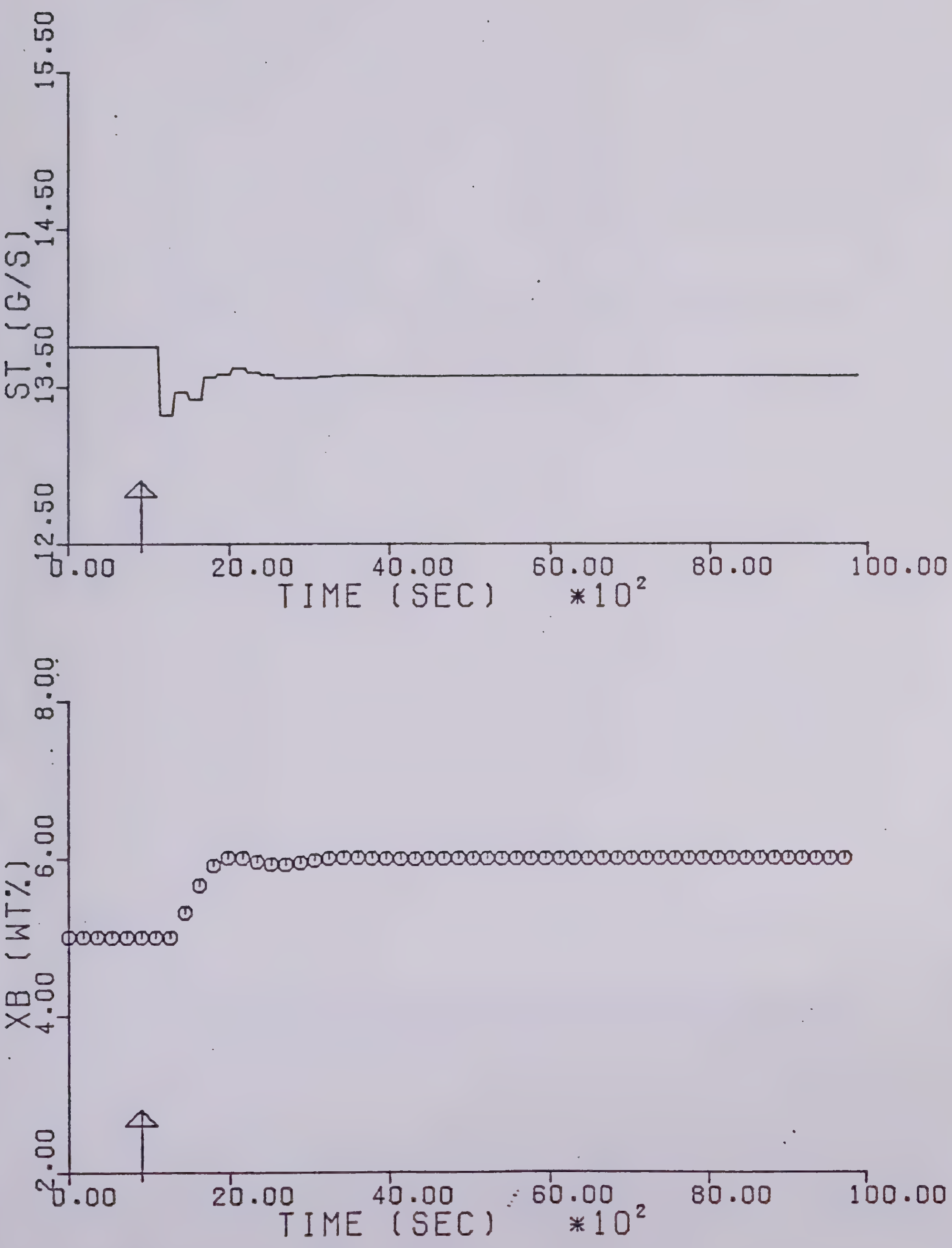


Figure 5.3.3 PID Algorithm Control of Bottom Composition for a +1% Step Change in Set Point (Run S-PID01; K_C = -0 198, K_I = -0.045, K_D = -0.192)

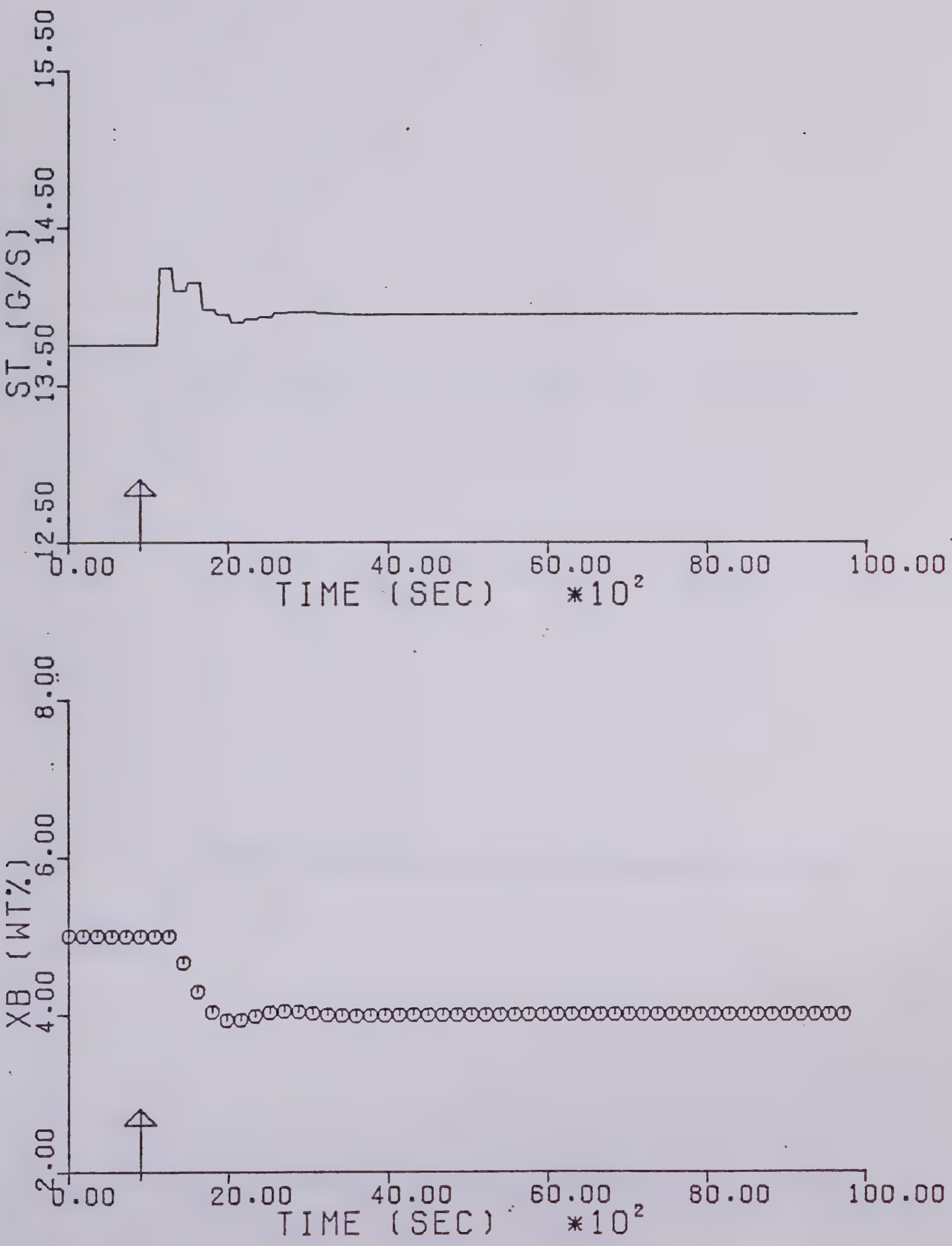


Figure 5.3.4 PID Algorithm Control of Bottom Composition for a -1% Step Change in Set Point (Run S-PID02; K_C = 0.240, K_I = -0.053, K_D = -0.197)

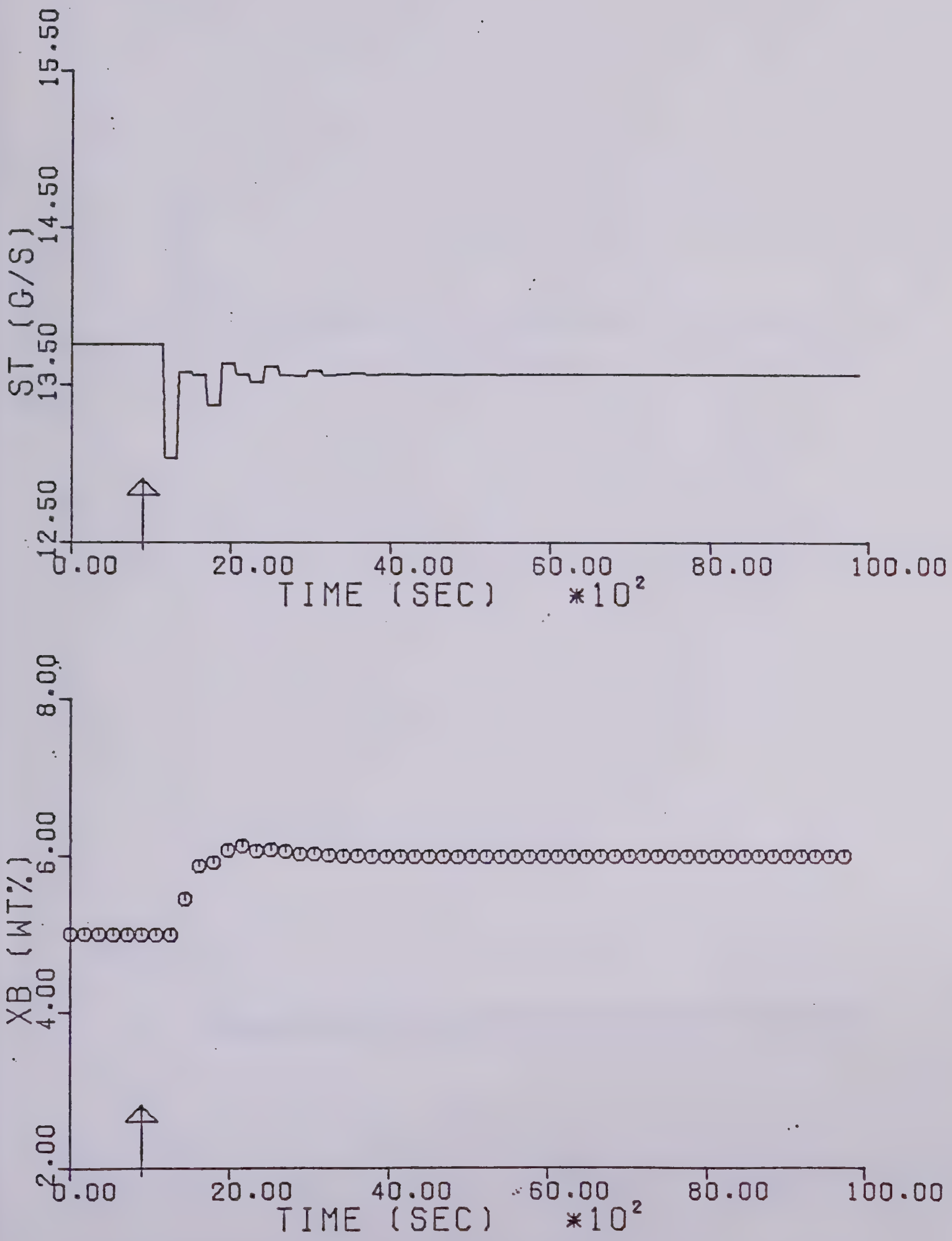


Figure 5.3.5 Deadbeat Algorithm Control of Bottom Composition for a +1% Step Change in Set Point (Run S-DB01; K_p = -5 24, T_p = 563.0, T_d = 187.0)

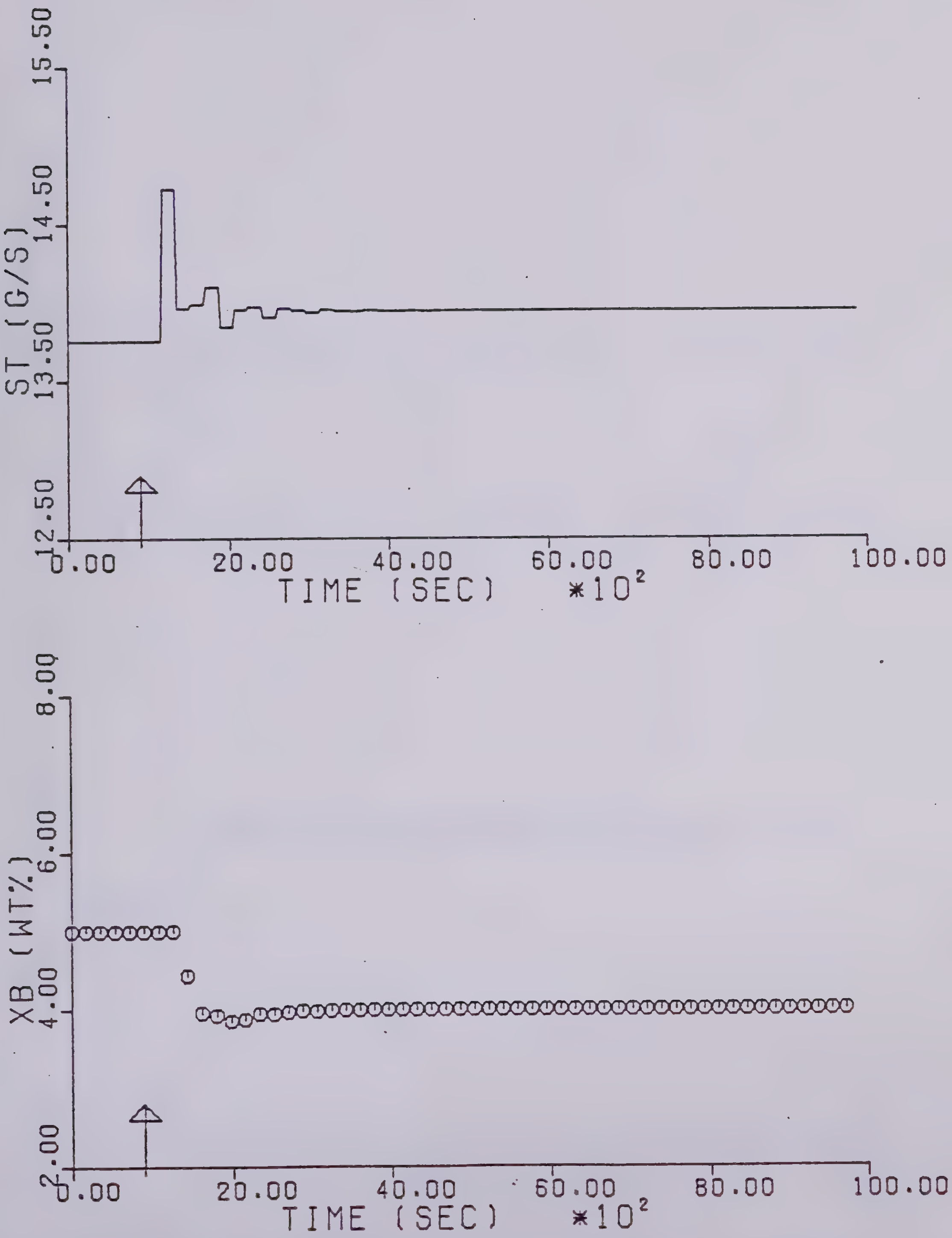


Figure 5.3.6 Deadbeat Algorithm Control of Bottom Composition for -1% Step Change in Set Point (Run S-DB02; K_p = -4.29, T_p = 633.0, T_d = 187.0)

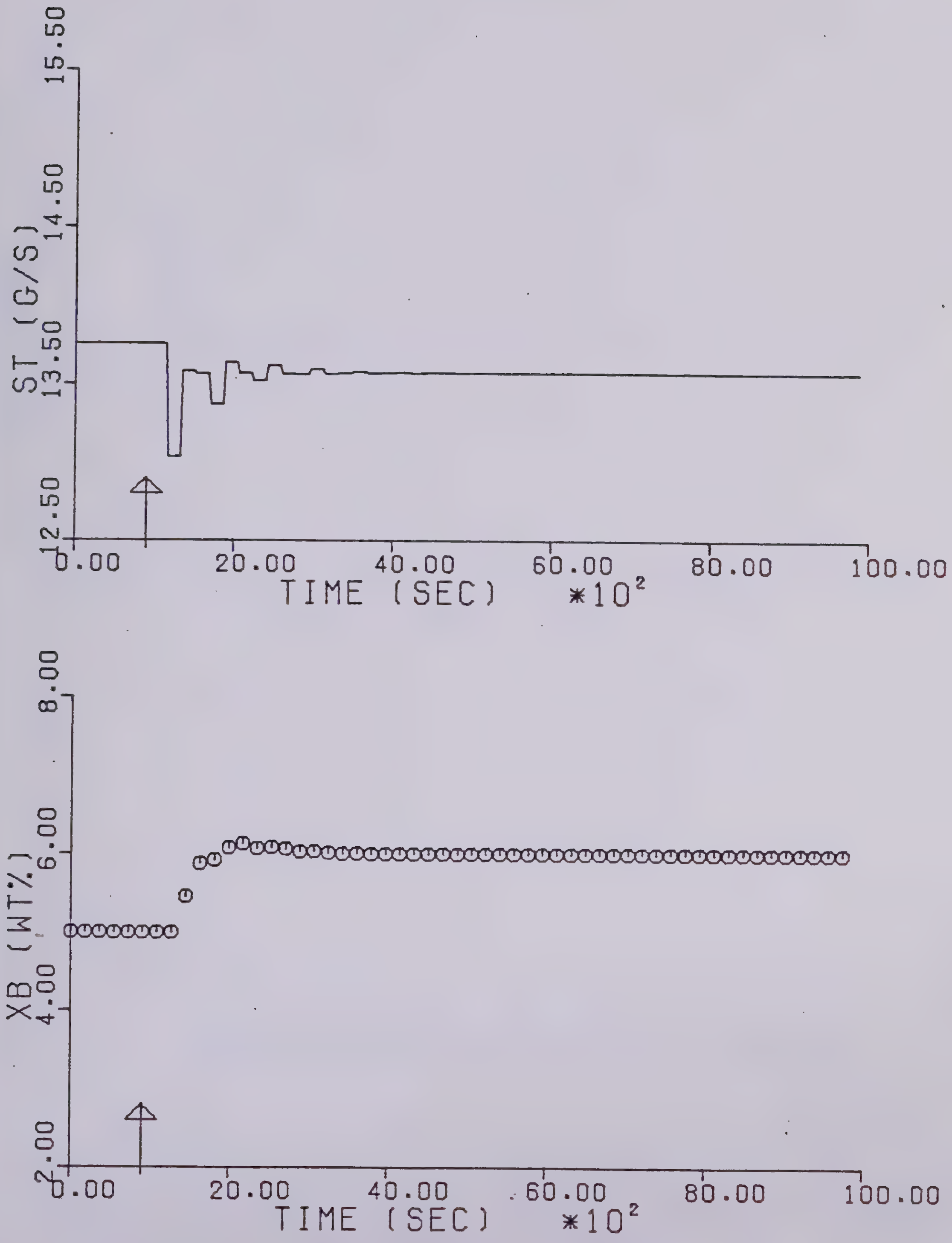


Figure 5.3.7 Dahlin Algorithm Control of Bottom Composition for +1% Step Change in Set Point (Run S-DAH01; $K_p = -5.24$, $T_p = 563.0$, $T_d = 187.0$, $\lambda = 14.0$)

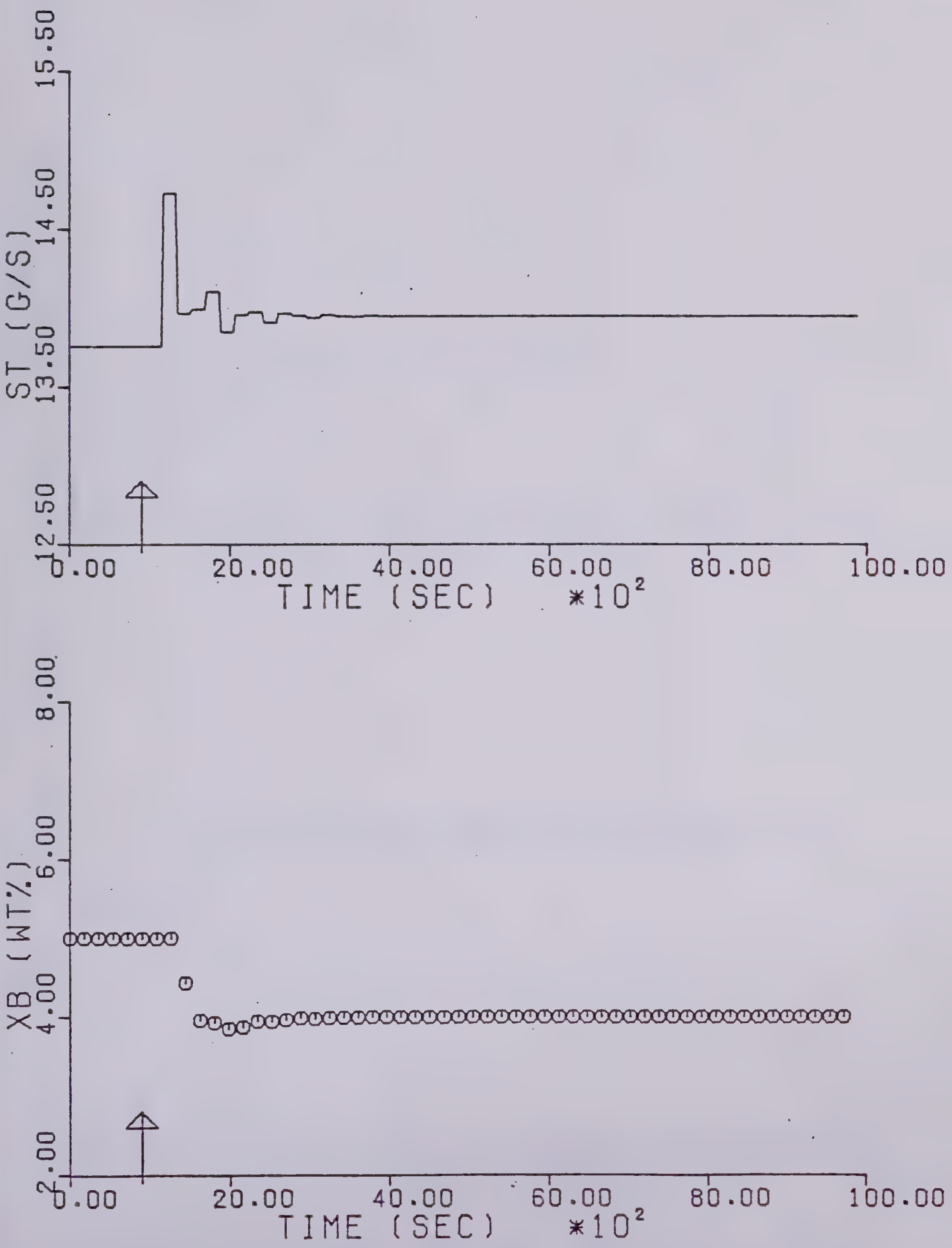


Figure 5.3.8 Dahlin Algorithm Control of Bottom Composition for -1% Step Change in Set Point (Run S-DB02 K_p = -4.29, T_p = 633.0, T_d = 187.0, λ = 20.0)

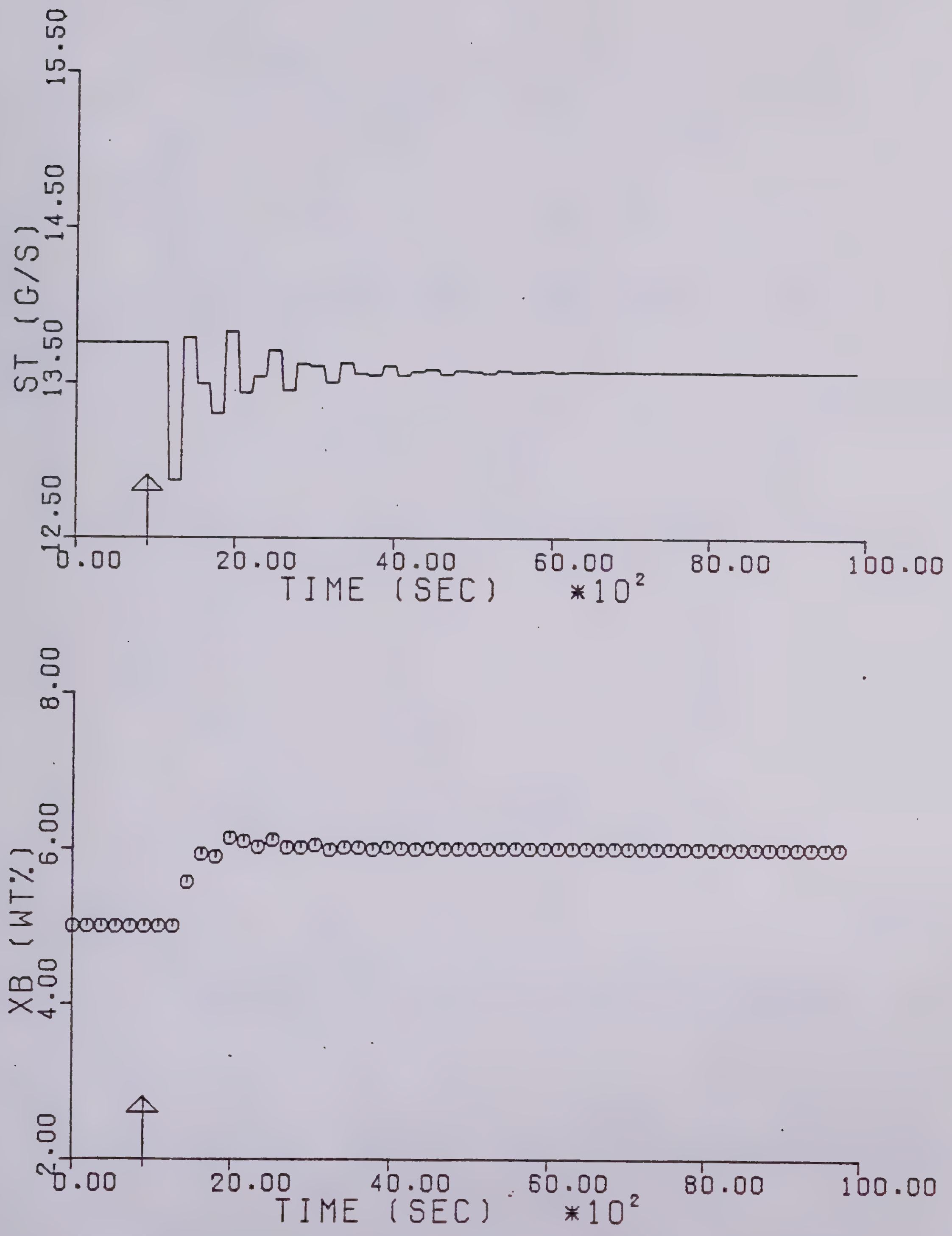


Figure 5.3.9 Smith Predictor Control of Bottom Composition for +1% Step Change in Set Point (Run S-SLP01 $K_p = -5.24$, $T_p = 563.0$, $T_d = 187.0$, $K_C = -0.678$, $K_I = -0.210$)

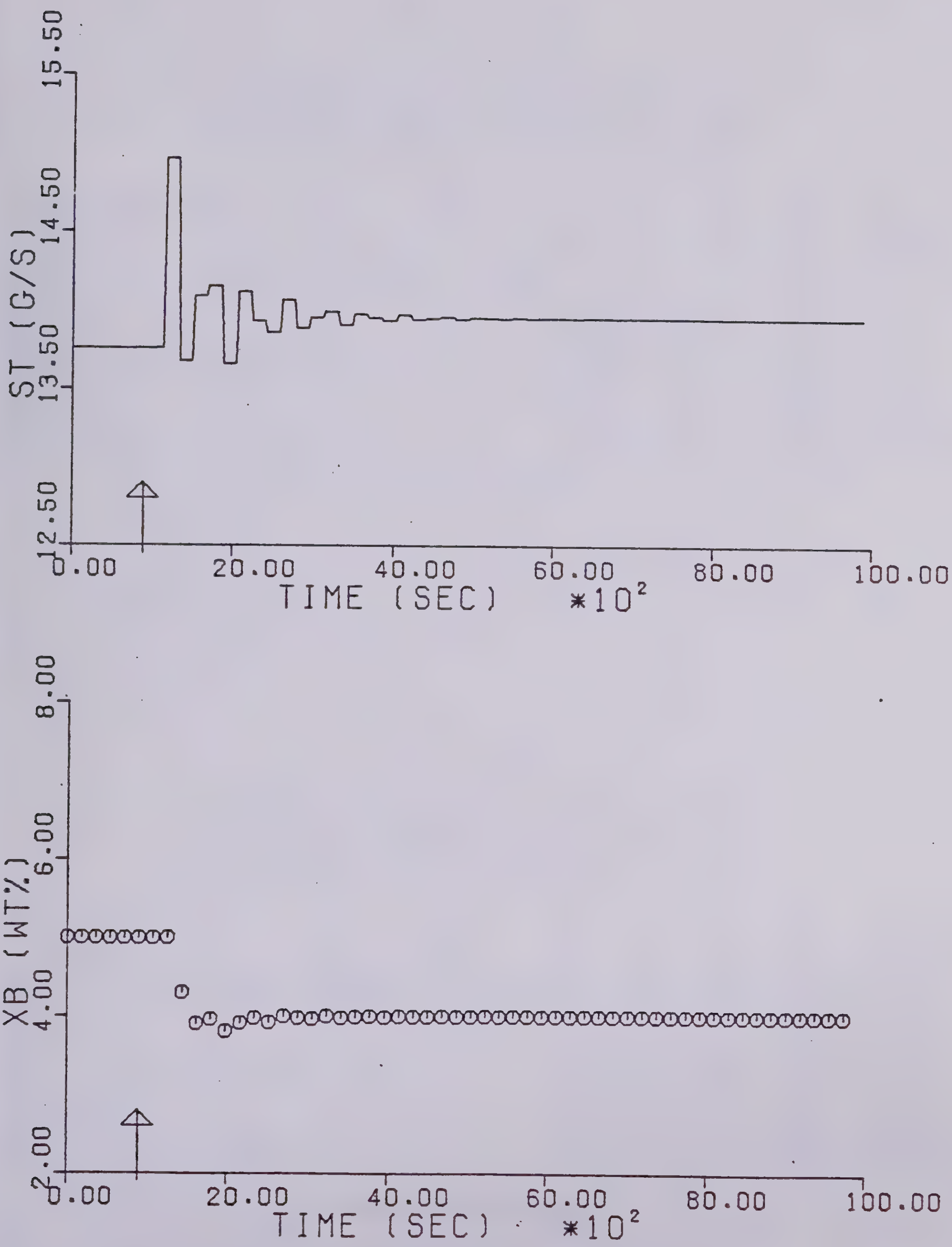


Figure 5.3.10 Smith Predictor Control of Bottom Composition for -1% Step Change in Set Point (Run S-SLP02; K_p = -4.29, T_p = 633.0, T_d = 187.0, K_C = -0.948, K_I = -0.263)

Table 5.4.1

Summary of Simulated Results for
Control of Bottom Composition for
a -25% Step Change in Feed Flow Rate

Algorithm	K_C	K_I	K_D	K_p	T_p	T_d	IAE	Figure
PI	-0.245	-0.064	—	—	—	—	6714	5.4.1
PID	-0.262	-0.101	-0.295	—	—	—	4746	5.4.3
Deadbeat	—	—	—	-4.29	633	187	5135	5.4.5
Dahlin	$\lambda = 20$s	—	—	-4.29	633	187	5135	5.4.7
Smith Pred.	-0.856	-0.911	—	-4.29	633	187	3923	5.4.9
Deadbeat*	—	—	—	-3.12	456	187	3803	5.4.11
Dahlin*	$\lambda = 167$s	—	—	-3.12	456	187	4659	5.4.13
Smith Pred.*	-0.856	-0.911	—	-3.12	456	187	3291	5.4.15

(*) - using improved tuning procedure

K_C = (g/s)/wt.%

K_I = (g/s)/(wt.%-s)

K_D = (g/s)/(wt.%/s)

IAE = wt.%-s

K_p = wt.%/(g/s)

T_p = s

T_d = s

Table 5.4.2

Summary of Simulated Results for
Control of Bottom Composition for
a +25% Step Change in Feed Flow Rate

Algorithm	K_C	K_I	K_D	K_p	T_p	T_d	IAE	Figure
PI	-0.267	-0.133	—	—	—	—	2714	5.4.2
PID	-0.319	-0.171	-0.324	—	—	—	2254	5.4.4
Deadbeat	—	—	—	-5.24	563	187	5381	5.4.6
Dahlin	$\lambda = 28$s	—	—	-5.24	563	187	5385	5.4.8
Smith Pred.	-0.534	-0.639	—	-5.24	563	187	4210	5.4.10
Deadbeat*	—	—	—	-1.87	352	187	1941	5.4.12
Dahlin*	$\lambda = 149$s	—	—	-1.87	352	187	2229	5.4.14
Smith Pred.*	-0.547	-0.623	—	-1.87	352	187	1939	5.4.16

(*) - using improved tuning procedure

K_C = (g/s)/wt.%

K_I = (g/s)/(wt.%-s)

K_D = (g/s)/(wt.%/s)

IAE = wt.%-s

K_p = wt.%/(g/s)

T_p = s

T_d = s

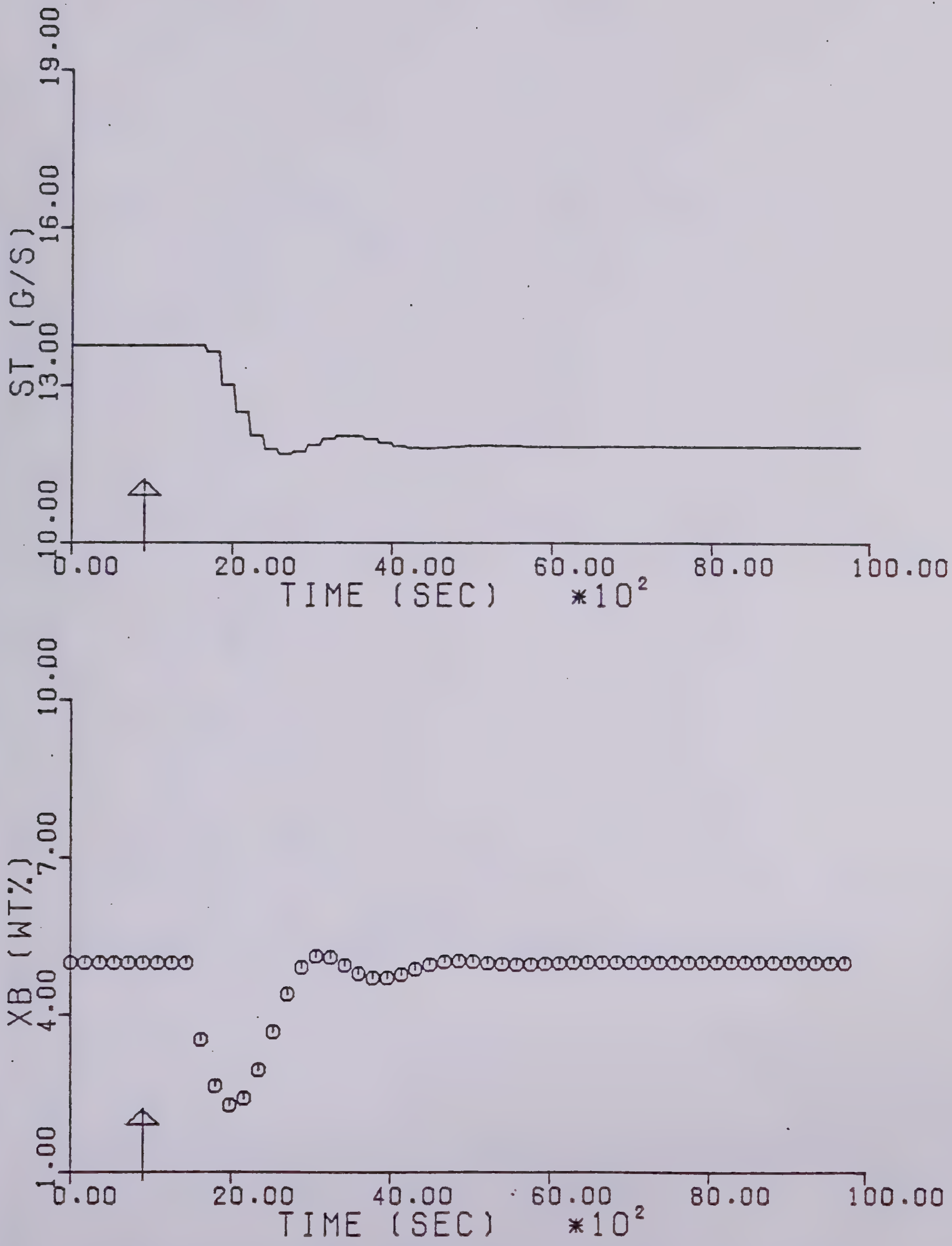


Figure 5.4.1 PI Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (Run S-PI03; K_C = -0.245, K_I = -0.064)

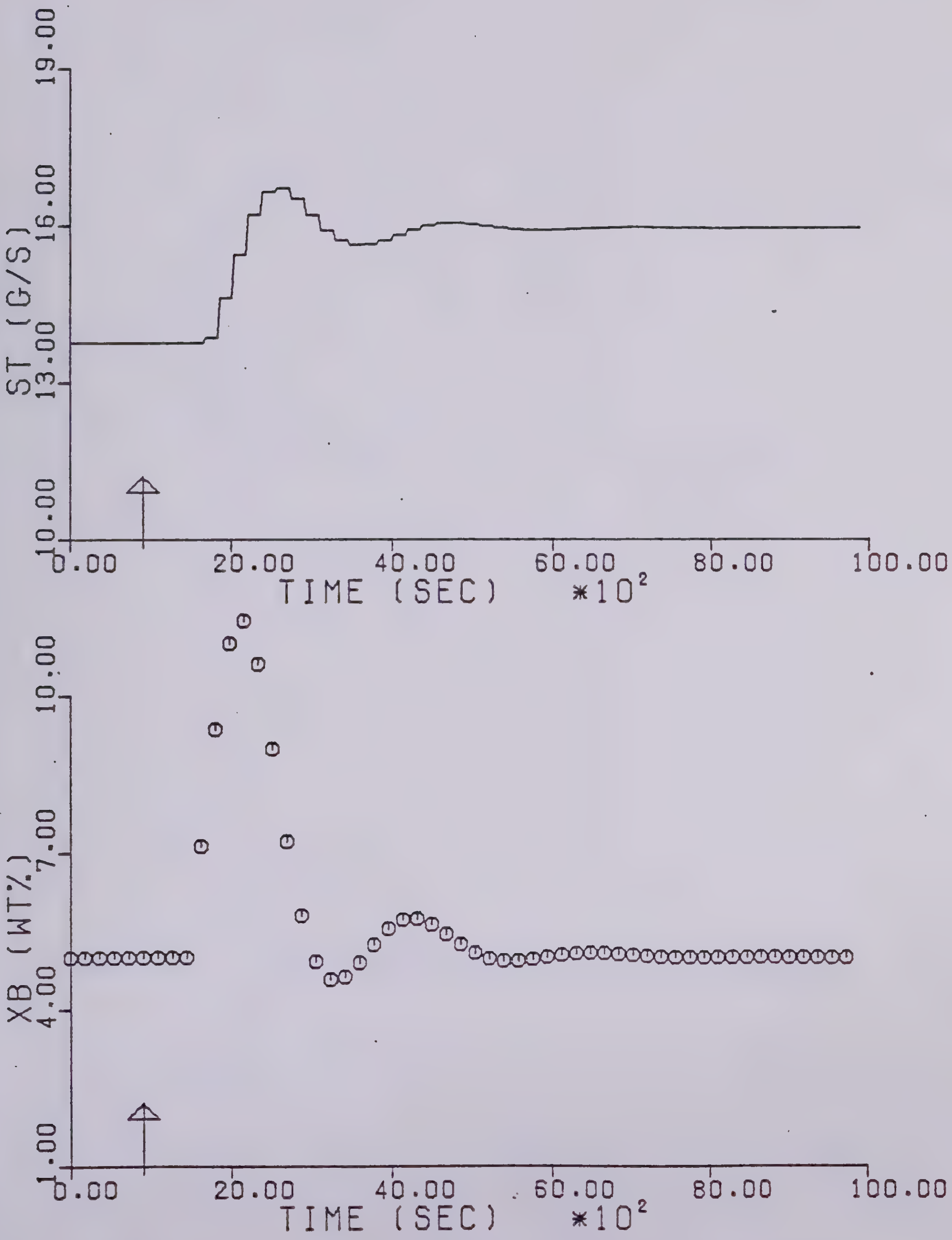


Figure 5.4.2 PI Algorithm Control of Bottom Composition for a +25% Step Change in Feed Flow Rate (Run S-PI04; K_C = -0.267, K_I = -0.133)

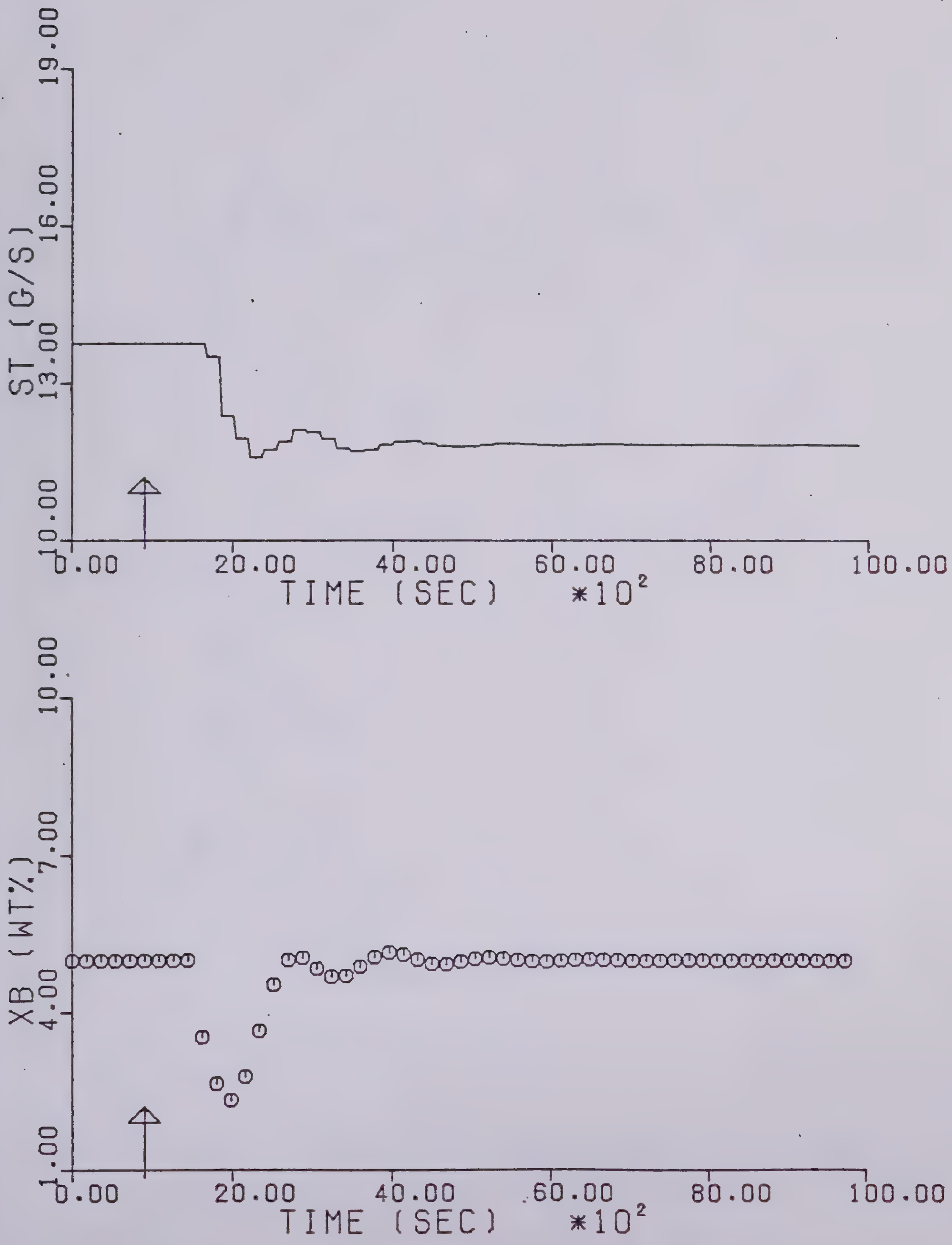


Figure 5.4.3 PID Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (Run S-PID03; K_C= -0.262, K_I= -0.101, K_D= -0.295)

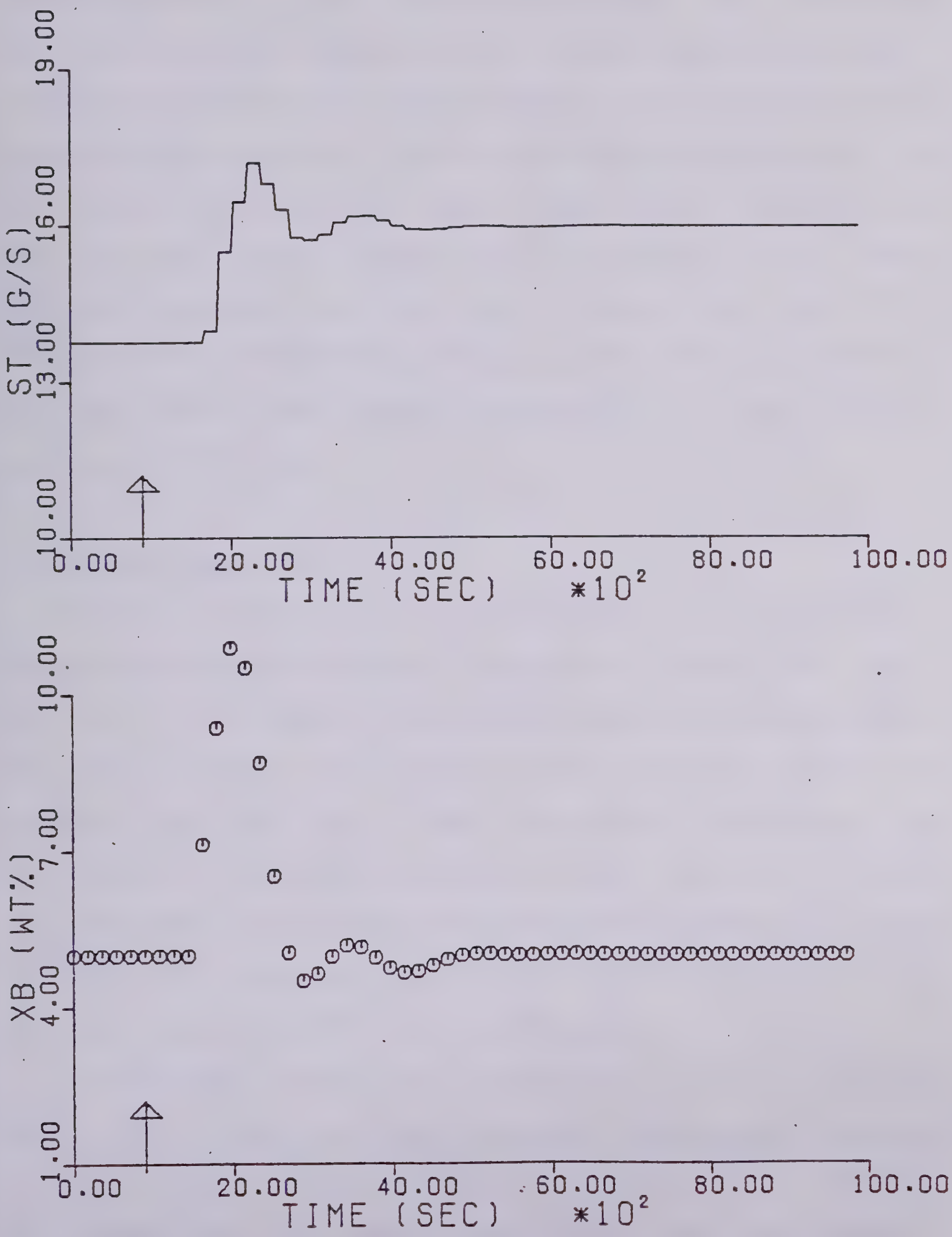


Figure 5.4.4 PID Algorithm Control of Bottom Composition for a +25% Step Change in Feed Flow Rate (Run S-PID04; K_C= -0.319, K_I= -0.171, K_D= -0.324)

parameters used for the servo control tests were those used for the regulatory control tests. Since unsatisfactory performance resulted using these parameters, an improved tuning procedure especially for these algorithms was developed. The performance with each of these algorithms as indicated by the lower IAE values, before and after the new tuning procedure was employed, are also given in Tables 5.4.1 and 5.4.2. The controlled composition responses using these algorithms, with and without the improved parameters, are shown in Figures 5.4.5 to 5.4.16.

5.5 Tuning Techniques

Tuning techniques for conventional PI and PID control algorithms have been reported by numerous workers (cf. Chapter 2). In this work, the correlations reported by Smith (51) were used to provided the initial sets of controller constants for both the PI and PID control algorithms. The procedure for adjusting the values of the constants to allow for the effect of sampling, as described by Smith (51), was followed. The final tuning constants were obtained by trial and error using the IAE value as the guide.

In the case of the Smith predictor, the initial values of K_C and K_I were calculated using the same models as used for the controller constant calculation for the PI controller except that the system time delay term was deleted. Again, the correlations from Smith (51) were used and the

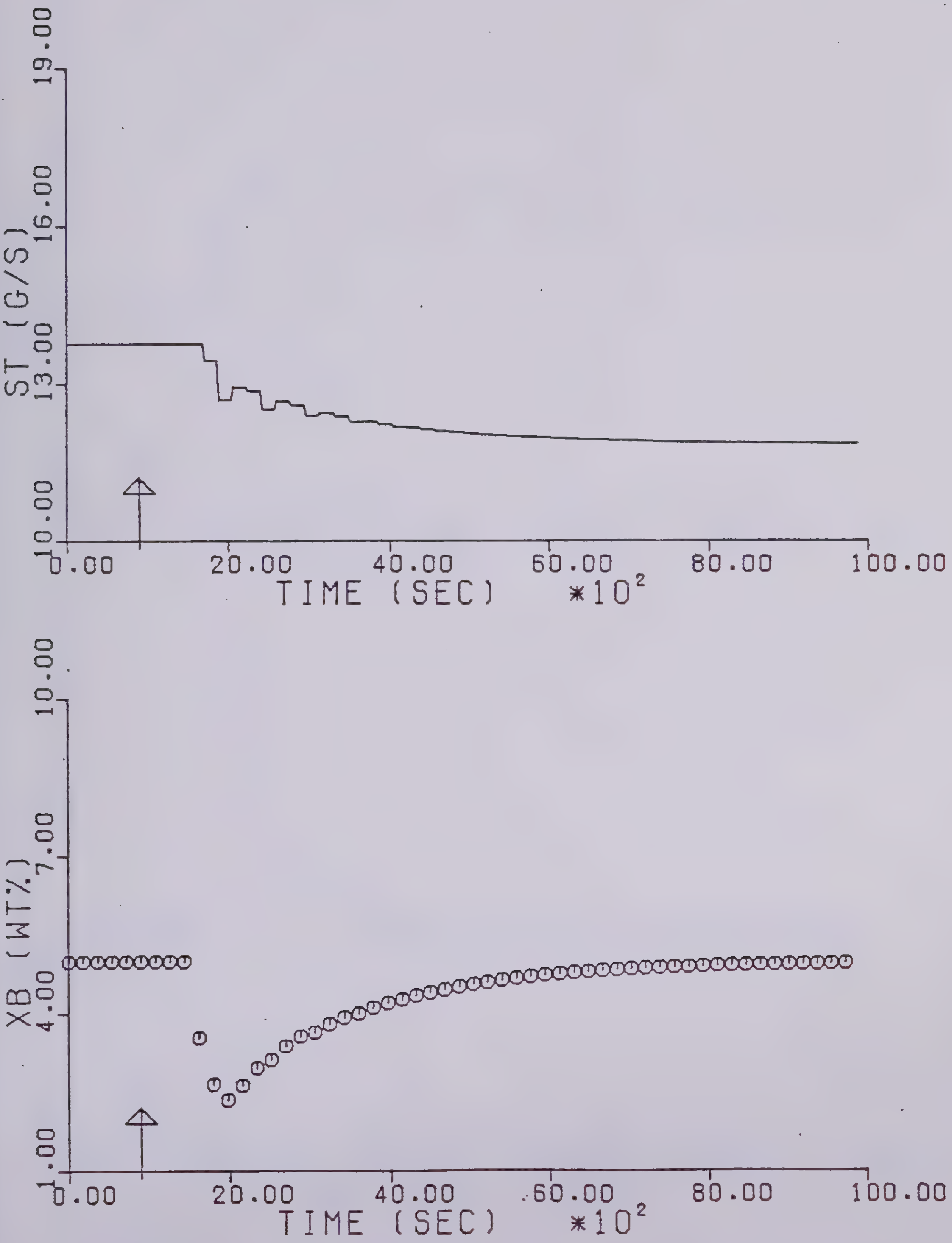


Figure 5.4.5 Deadbeat Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run S-DB03; $K_p = -4.29$, $T_p = 633.0$, $T_d = 187.0$)

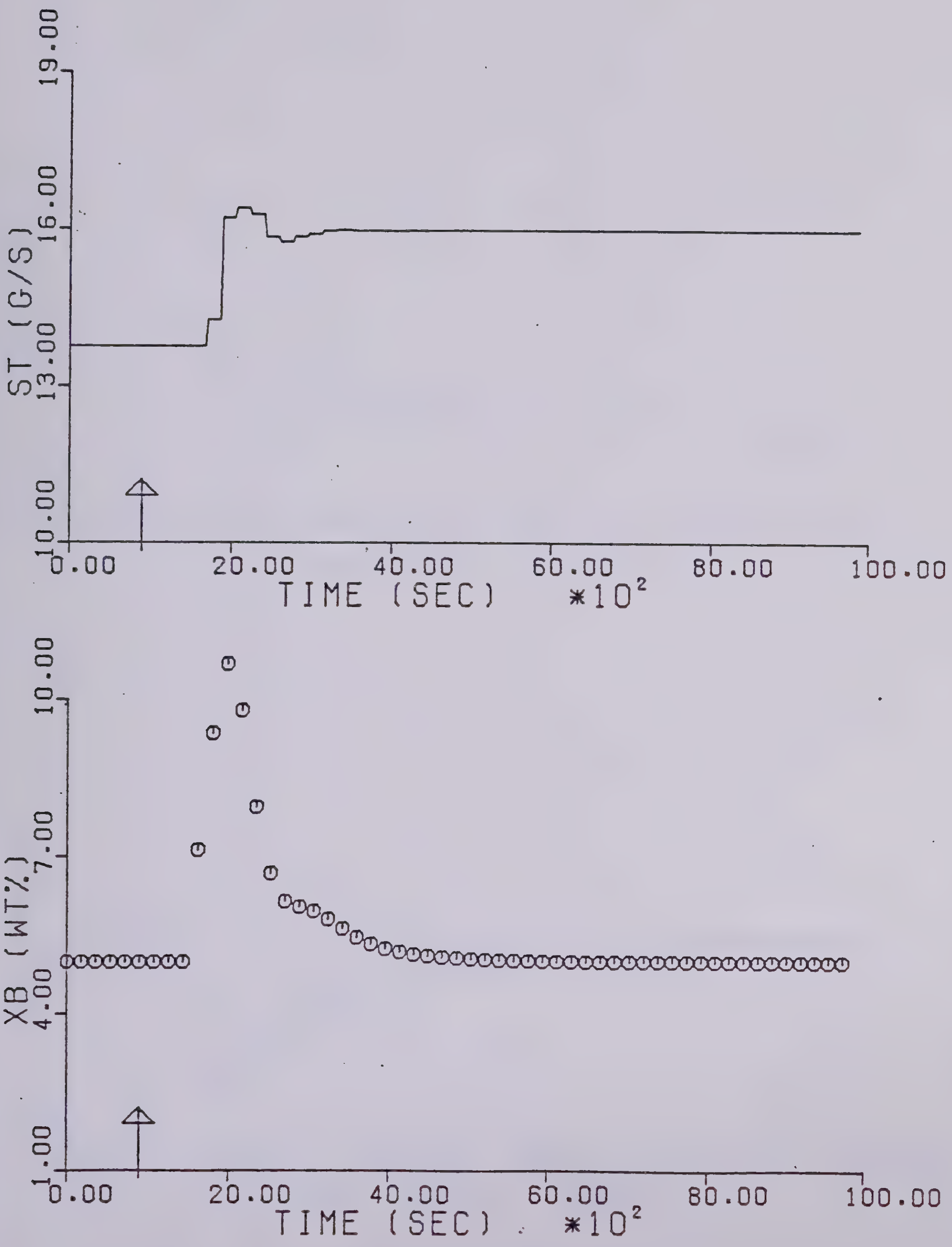


Figure 5.4.6 Deadbeat Algorithm Control of Bottom Composition for +25% Step Change in Feed Flow Rate (Run S-DB04; K_p = -5.24, T_p = 563.0, T_d = 187.0)

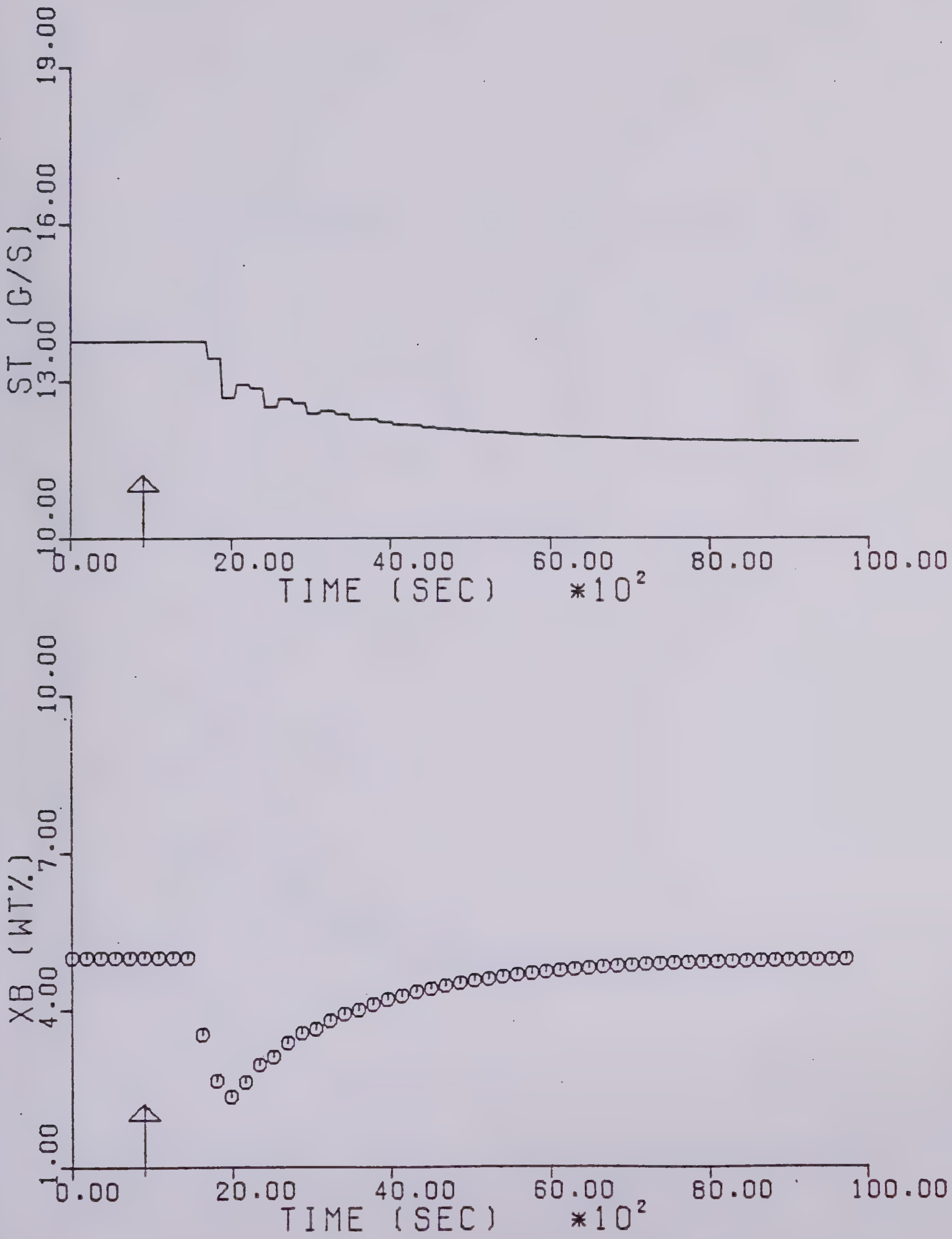


Figure 5.4.7 Dahlin Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run S-DAH03; $K_p = -4.29$, $T_p = 633.0$, $T_d = 187.0$, $\lambda = 20.0$)

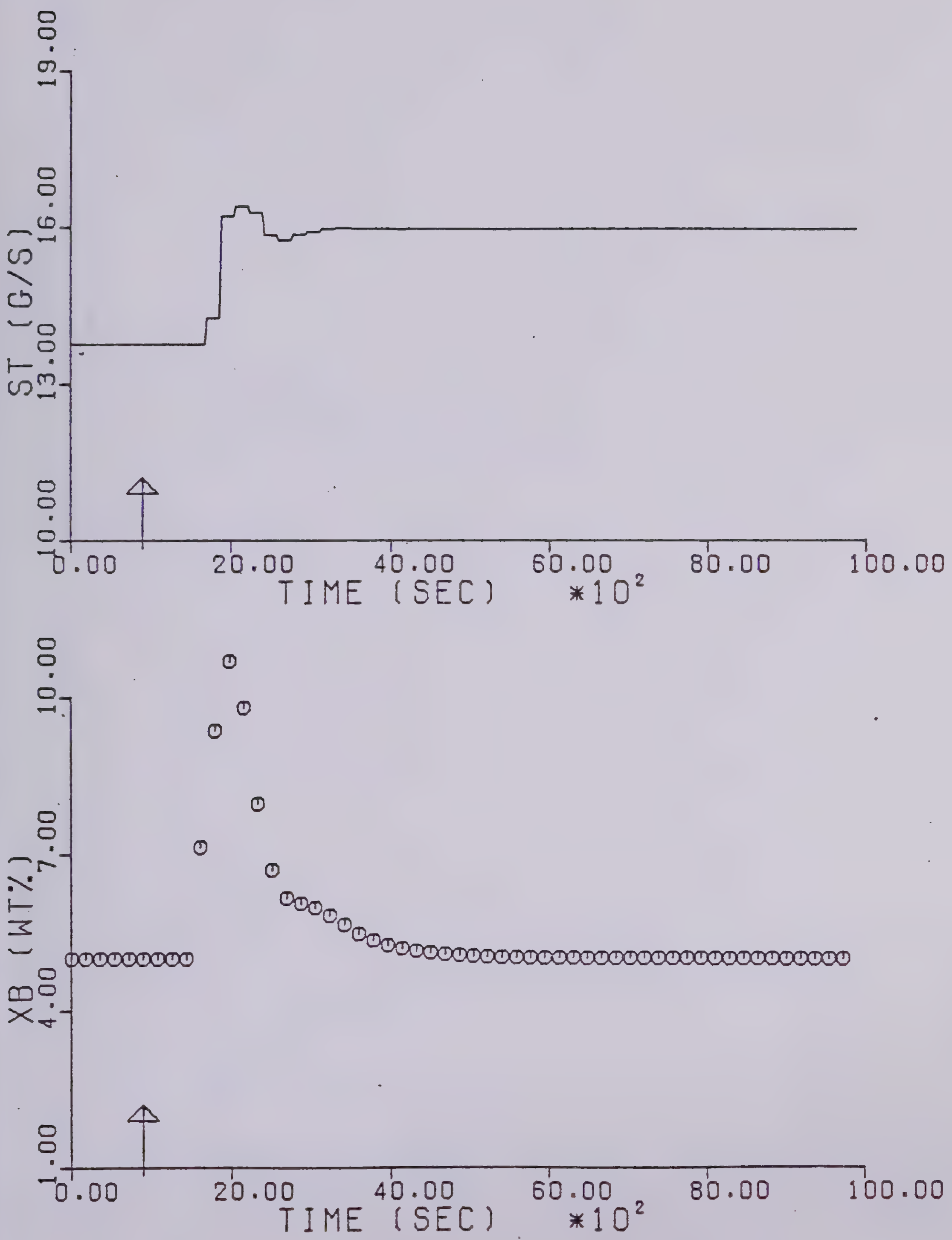


Figure 5.4.8 Dahlin Algorithm Control of Bottom Composition for +25% Step Change in Feed Flow Rate (Run S-DAH04; $K_p = -5.24$, $T_p = 563.0$, $T_d = 187.0$, $\lambda = 28.0$)

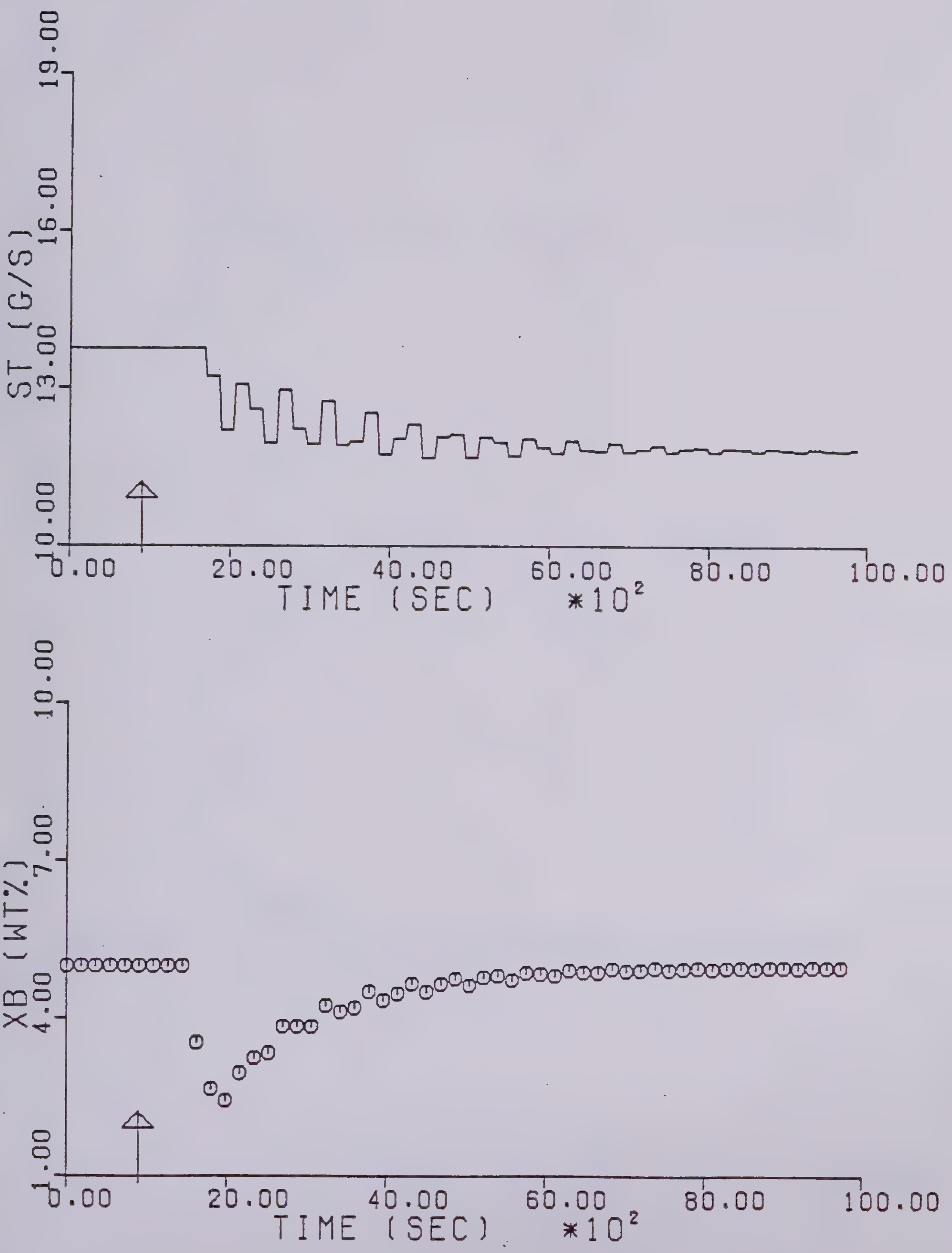


Figure 5.4.9 Smith Predictor Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run S-SLP03; $K_p = -4.29$, $T_p = 633.0$, $T_d = 187.0$, $K_C = -0.856$, $K_I = -0.911$)

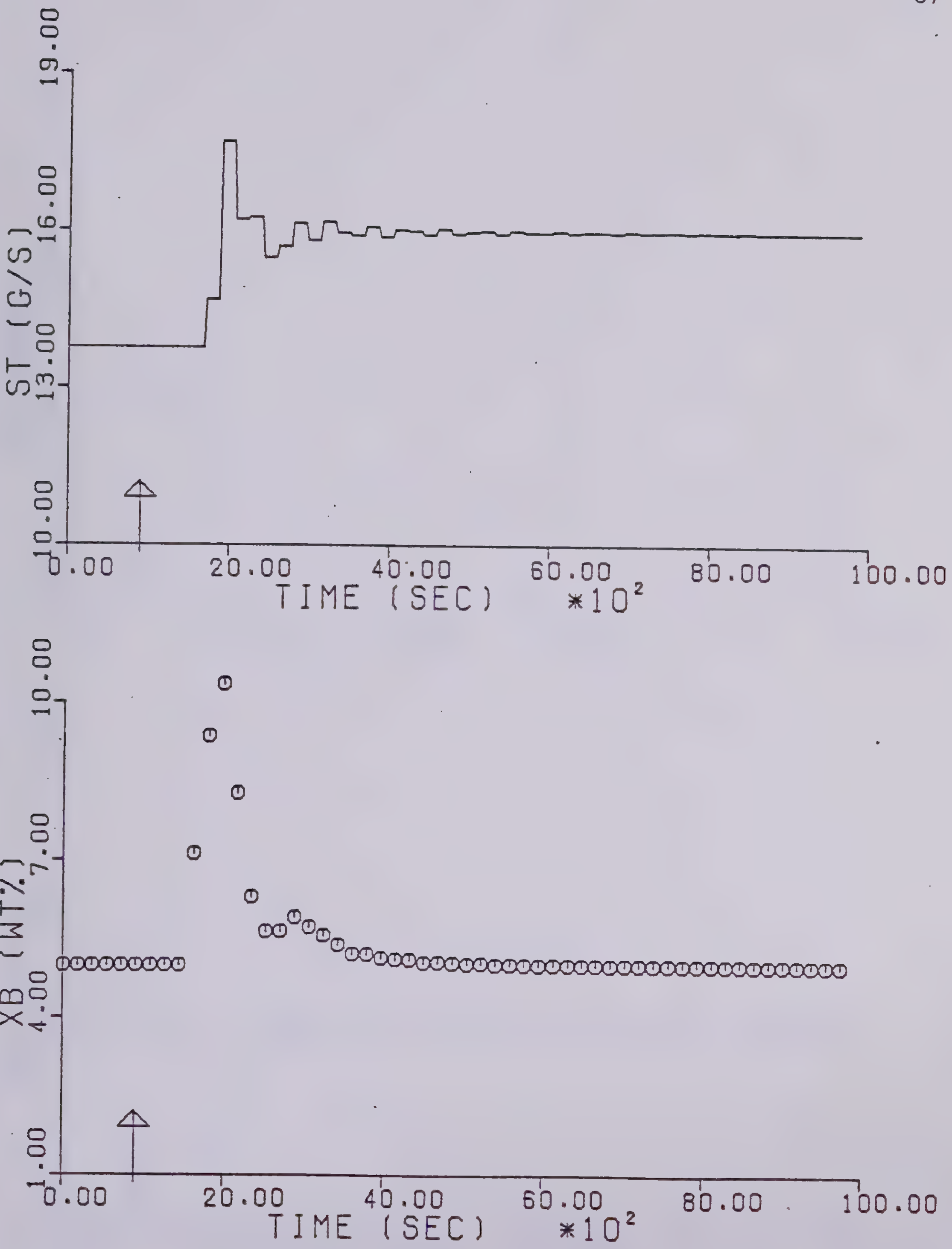


Figure 5.4.10 Smith Predictor Control of Bottom Composition for +25% Step Change in Feed Flow Rate (Run S-SLP04; $K_p = -5.24$, $T_p = 563.0$, $T_d = 187.0$, $K_C = -0.534$, $K_I = -0.639$)

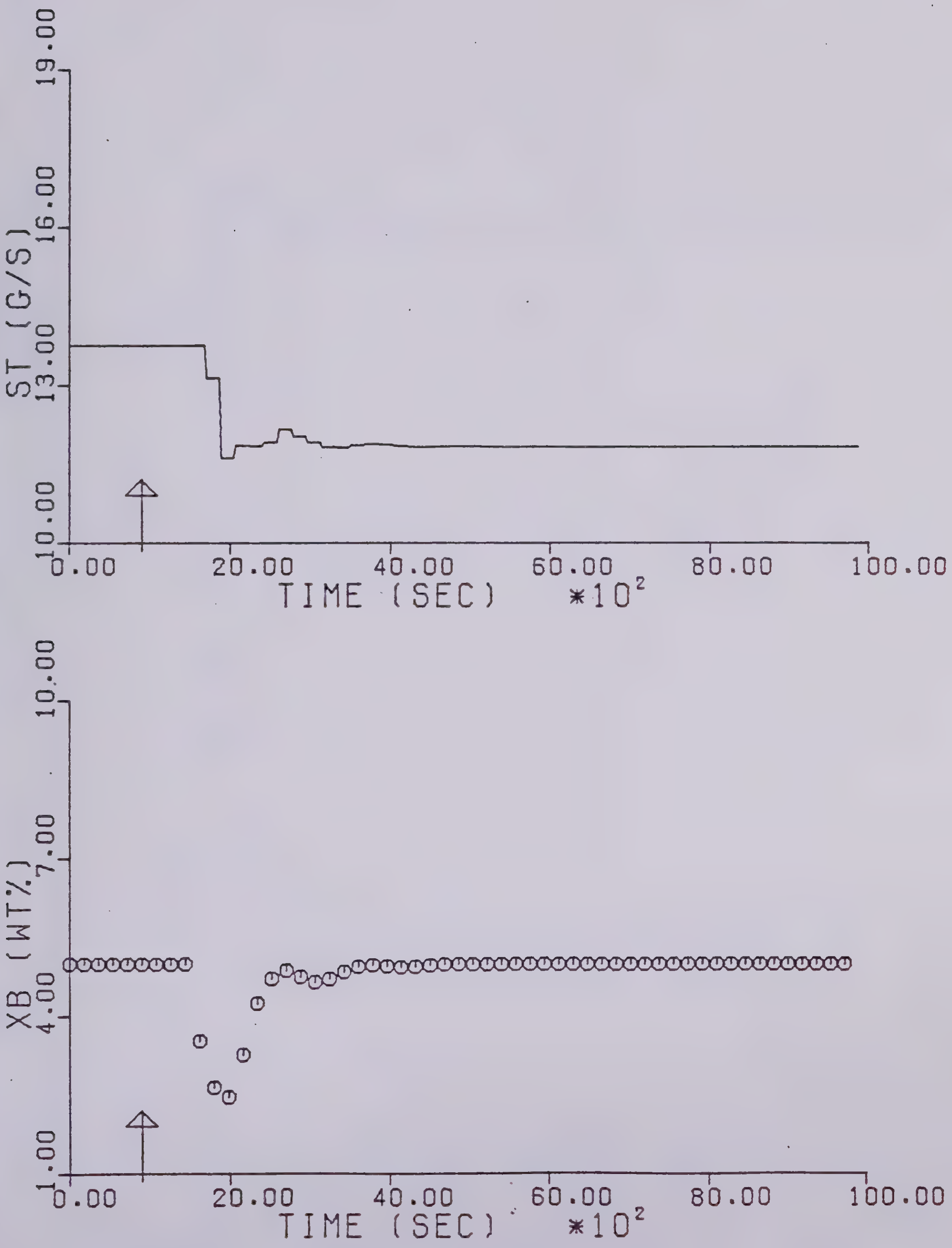


Figure 5.4.11 Deadbeat Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run S-DB05; K_p = -3.12, T_p = 456.0, T_d = 187.0)

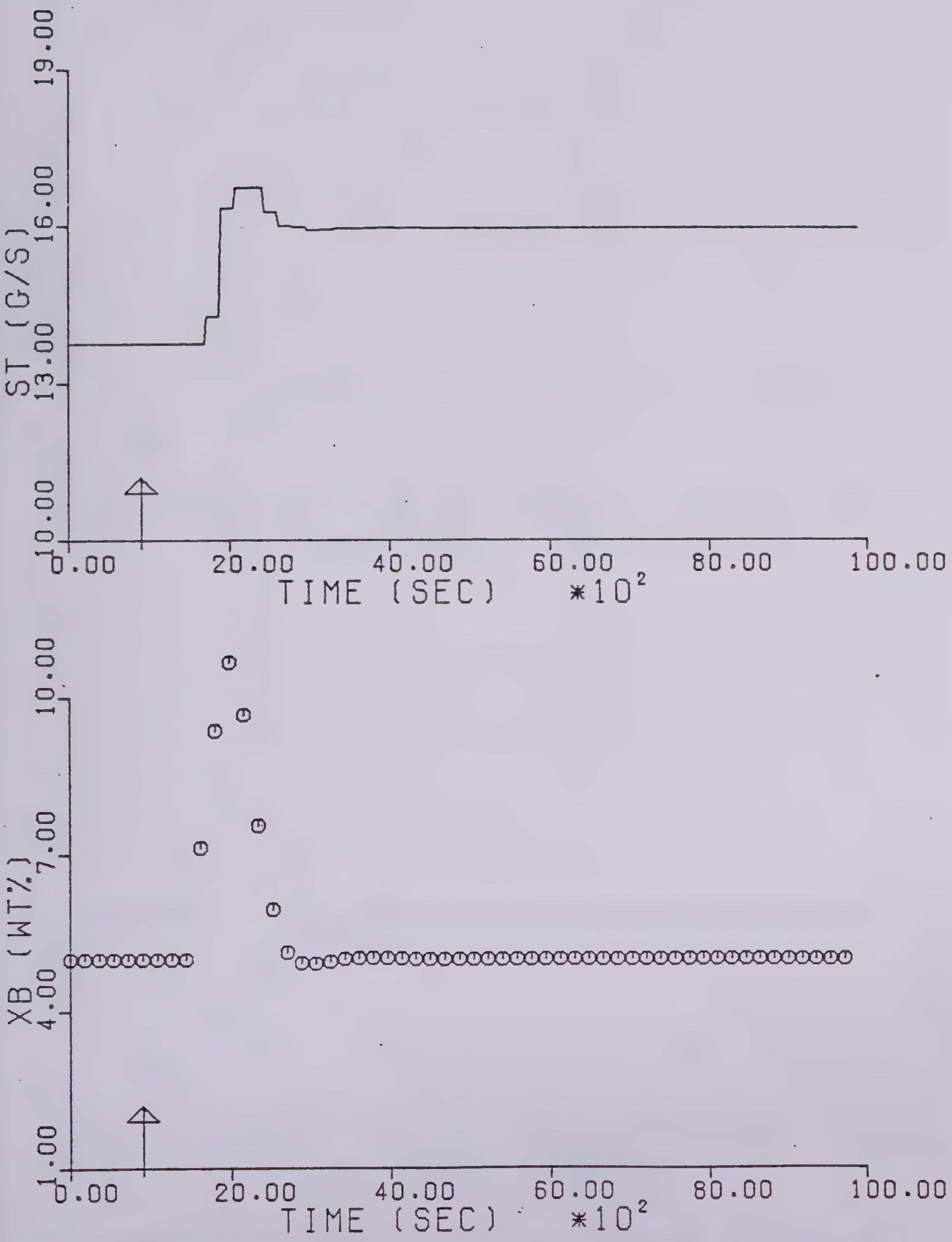


Figure 5.4.12 Deadbeat Algorithm Control of Bottom Composition for +25% Step Change in Feed Flow Rate (Run S-DB06; $K_p = -1.87$, $T_p = 352.0$, $T_d = 187.0$)

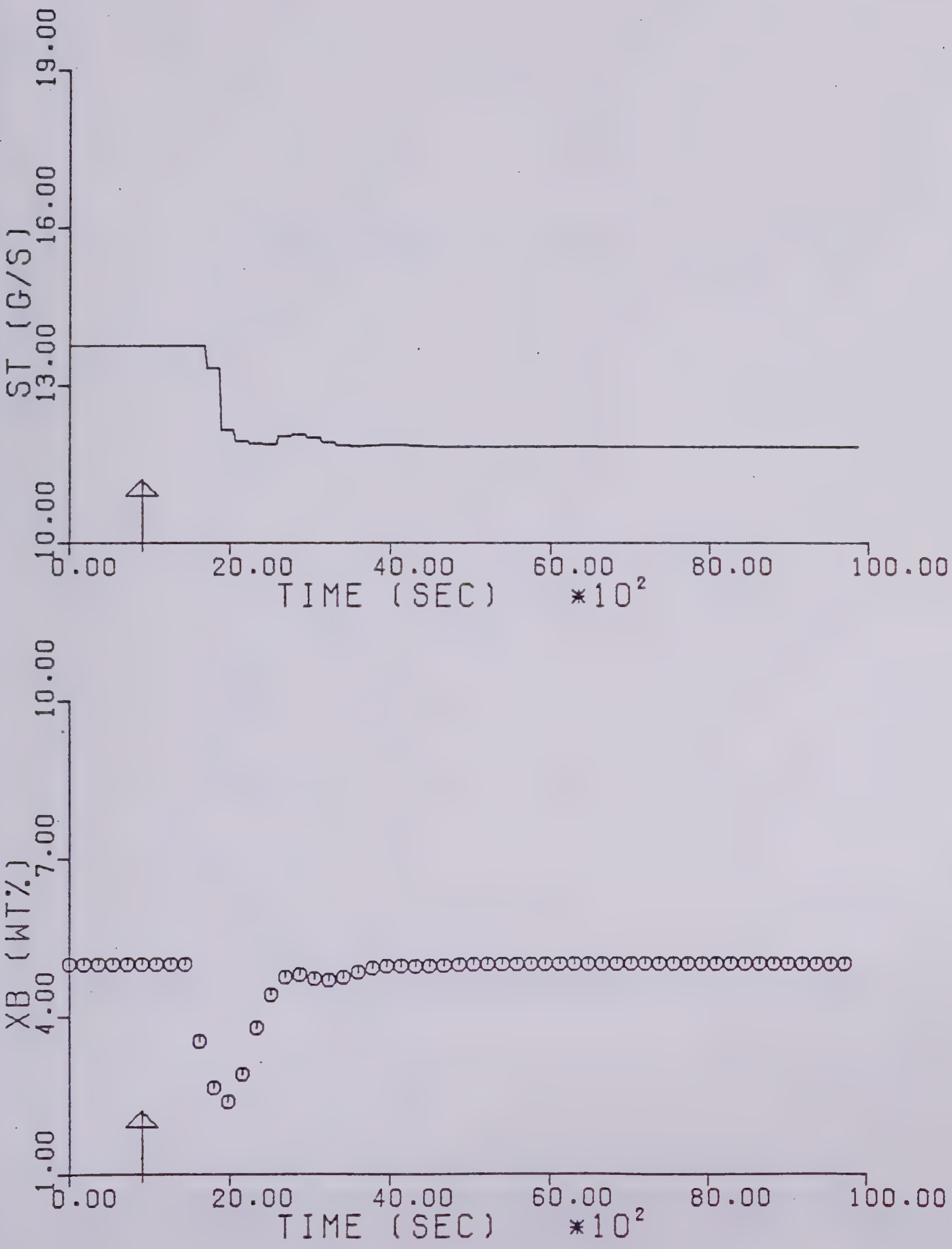


Figure 5.4.13 Dahlin Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run S-DAH05; K_p = -3.12, T_p = 456.0, T_d = 187.0, λ = 167.0)

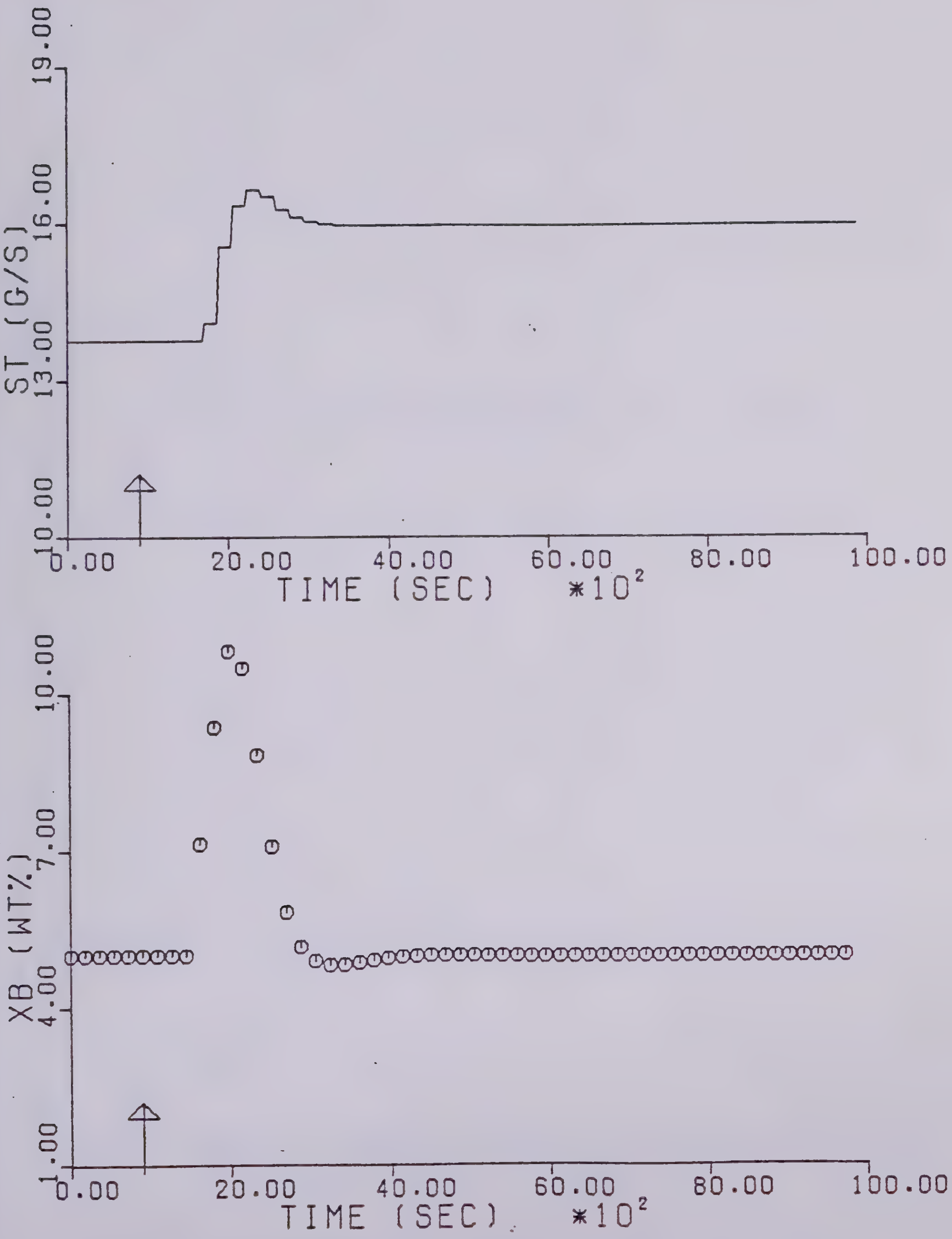


Figure 5.4.14 Dahlin Algorithm Control of Bottom Composition for +25% Step Change in Feed Flow Rate (Run S-DAH06; $K_p = -1.87$, $T_p = 352.0$, $T_d = 187.0$, $\lambda = 149.0$)

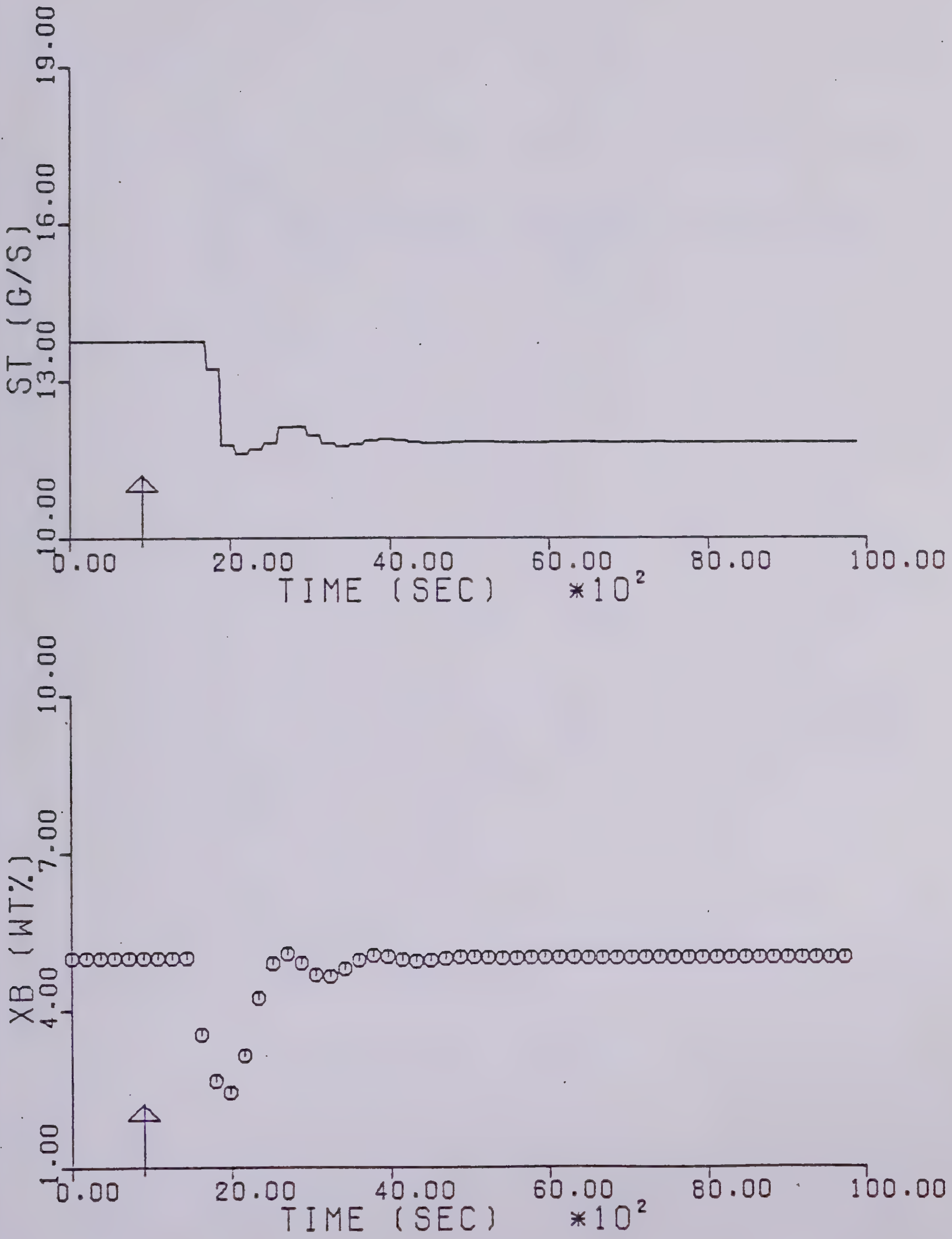


Figure 5.4.15 Smith Predictor Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run S-SLP05; $K_p = -3.12$, $T_p = 456.0$, $T_d = 187.0$, $K_C = -0.856$, $K_I = -0.911$)

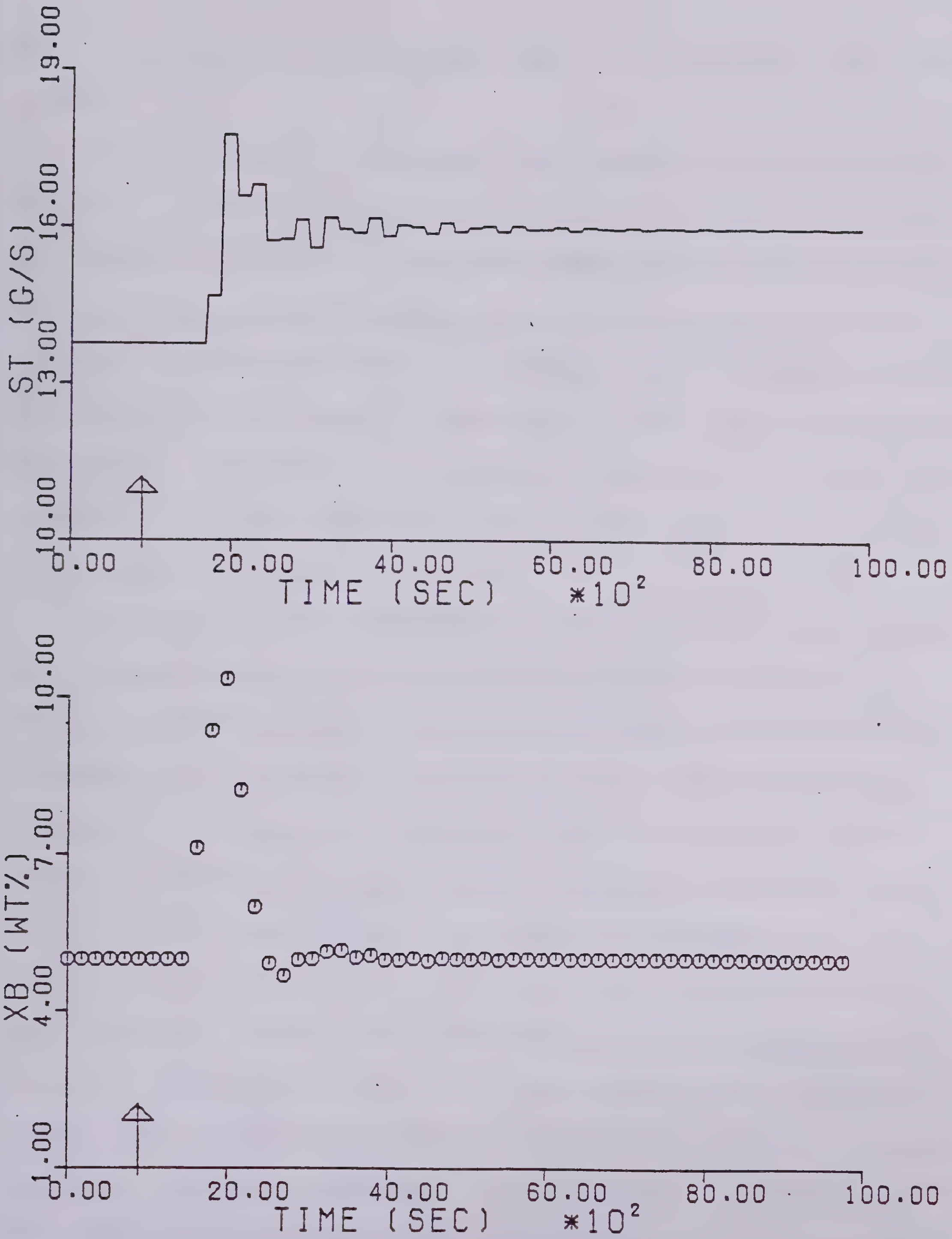


Figure 5.4.16 Smith Predictor Control of Bottom Composition for +25% Step Change in Feed Flow Rate (Run S-SLP06; $K_p = -1.87$, $T_p = 352.0$, $T_d = 187.0$, $K_C = -0.547$, $K_I = -0.623$)

tuning procedure followed was that of minimizing the IAE value.

For the Dahlin algorithm, the initial tuning involved setting λ, the time constant of the desired closed loop servo controlled response, to be the same value as the value of T_p, the time constant of the process. In the subsequent tuning, the desired performance is obtained by adjusting λ with the control performance improving as the value of λ is decreased. The effect of varying the value of λ on the response of the controlled and manipulated variable is illustrated in Figure 5.5.1.

From the digital simulation studies, it had been found that conventional tuning techniques as described above cannot be used to further tune the parameters of the Dahlin algorithm and the Smith predictor to yield satisfactory performance for regulatory control. This is shown by the IAE values in Tables 5.4.1 and 5.4.2. Since the deadbeat algorithm has the same general structure as the other two algorithms except that no provision exists for convenient adjusting parameter values, the performance of the deadbeat algorithm is governed strictly by the process model parameter values used in the algorithm. A sensitivity analysis on the influence of model parameter values on the performance of the deadbeat algorithm, can provide guidance as to the type of tuning procedure that might be appropriate for improving the performance of all three algorithms. Since the time delay of the process can be estimated quite accurately, only

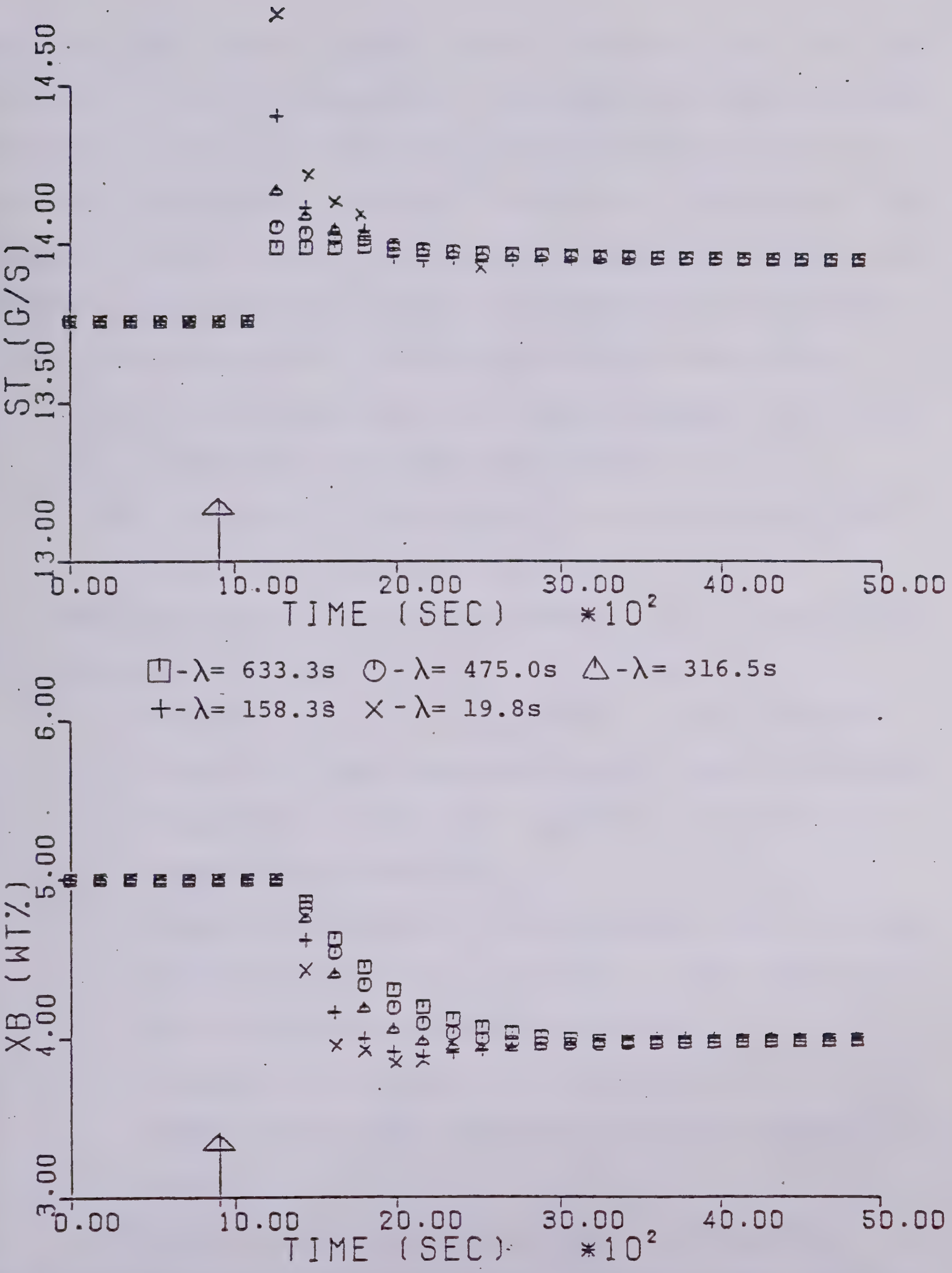


Figure 5.5.1 Effect of the value of λ in the Dahlin Algorithm on the Response of the Controlled and Manipulateed Variables for a -1% Step Change in Set Point

the influence of the values of the process gain and time constant on the performance of the deadbeat algorithm were studied. A summary of the results from the sensitivity analysis on the deadbeat algorithm is given in Table 5.5.1. As shown by these results, the model parameters used in the deadbeat algorithm can in fact be treated as tuning parameters. The performance of the deadbeat algorithm improves if:

1) the process gain is underestimated, up to 15% lower than the true value; and/or
2) the process time constant is overestimated, up to 15% higher than the true value.

On the basis of these observations, the following tuning procedure for regulatory control is recommended:

1) adjust the tuning parameters in the algorithm, e.g. λ in the Dahlin algorithm, until no further improvement (for the deadbeat algorithm, this step will be omitted);
2) adjust the process gain constant used in the model to improve the response of the system until no further improvement is possible;
3) adjust the process time constant used in the model in the same fashion described in Step (2); and
4) repeat steps (1), (2) and (3) if necessary.

By adopting this tuning procedure, it was found that by adjusting K_p and T_p of the process model used in the deadbeat, Dahlin and Smith predictor algorithms, a significant

Table 5.5.1

Sensitivity Analysis of the Influence of Model Parameters on the Performance of the Deadbeat Control Algorithm (T_d = 187s)

% Deviation From Actual Value	-30%	-15%	0%	+15%	+30%
	IAE	IAE	IAE	IAE	IAE
K_p	784	689	721	768	806
T_p	951	826	721	629	629
K_p and T_p	877	762	721	684	694

K_p = wt.%/(g/s)

T_p = s

IAE = wt.%-s

improvement in their control performance for regulatory control resulted (cf. Figure 5.5.2). A summary showing the progression of tuning the model parameters in the deadbeat algorithm using this technique is given in Table 5.5.2. A comparison of the transient responses of the composition control achieved using different model parameters is shown in Figure 5.5.2.

5.6 Discussion of Simulated Control Performance

For servo control operation, using the IAE value as the performance criterion, the deadbeat algorithm gave the best control performance and the Dahlin algorithm provided almost the equivalent performance since it was tuned in a manner

Table 5.5.2

Summary of Simulated Results for Deadbeat Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (T_d = 187s)

RUN	K_p (wt.%/g/s)	T_p (s)	IAE (wt%-s)
S-DB04	-5.24	563	5382
S-DB30	-4.54	563	4594
S-DB31	-3.78	563	3913
S-DB32	-3.21	563	3328
S-DB33	-2.73	563	2832
S-DB34	-2.32	563	2426
S-DB35	-1.97	563	3869
S-DB36	-2.44	563	2532
S-DB37	-2.20	563	2480
S-DB38	-2.32	591	2516
S-DB39	-2.32	535	2408
S-DB40	-2.32	508	2408
S-DB41	-2.32	483	2408
S-DB42	-1.87	352	1941

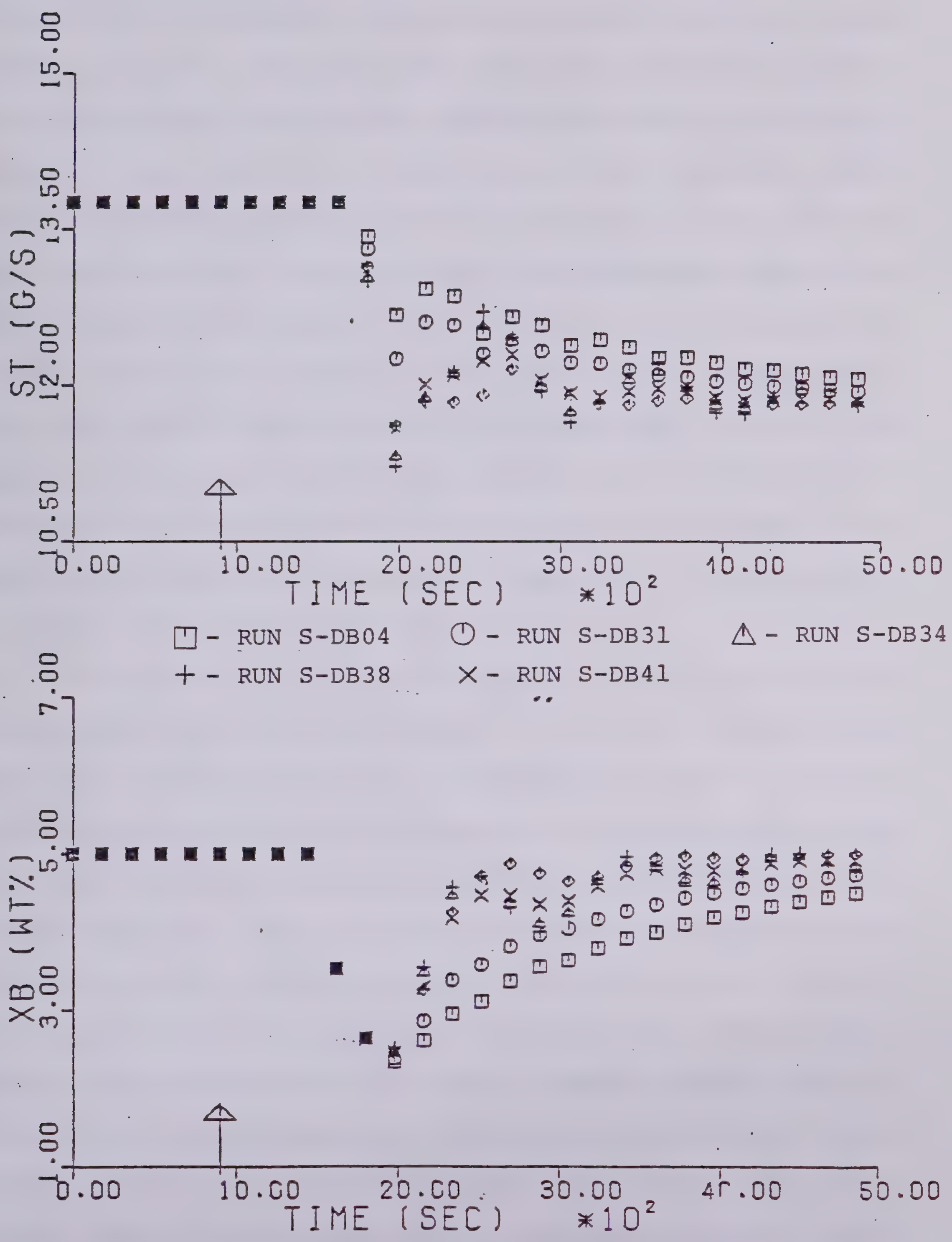


Figure 5.5.2 Effect of Algorithm Constants in the Deadbeat Algorithm on the Response of the Controlled and Manipulated Variables for a -25% Step Change in Feed Flow Rate

similar to that used for the deadbeat algorithm, i.e. a very small value of . The IAE value for Smith predictor control is very close to those of the deabeat and Dahlin algorithms, however, the response of the manipulated variable under Smith predictor control is more oscillatory than was the case for the other two algorithms. The deterioration in the performance of both the PI and PID algorithms is mainly due to the significant amount of time delay in the system (process and sample time of the gas chromatograph). However, it must be noted that derivative action provides significant compensation for the time delay as shown by the much lower IAE value using the PID algorithm compared to the value that resulted using the PI algorithm.

In the case of regulatory control, using a conventional tuning technique, the performance of both the deadbeat and Dahlin algorithm was inferior to that of a tuned PID algorithm when the system was subjected to a +25% step disturbance in feed flow rate. Furthermore, their performance was even worse than that obtained using the PI algorithm when the disturbance was a 25% decrease in feed flow rate. The performance of the Smith predictor for regulatory control operation also deteriorated in a similar manner. Meyer (37) observed that the performance of the Smith predictor for regulatory control is dependent on the ratio of the time constants of the process and load disturbance transfer functions even though the algorithm is designed to cancel the time delay term in the closed loop system characteristic

equation. In this work, it was found that for regulatory control, the performance of the deadbeat, Dahlin and Smith predictor algorithms using conventional tuning techniques is unsatisfactory when the time constant of the process is much larger than that of the load transfer function. In the other words, part or all of the effect of the load disturbance on the process controlled variables results before the control action takes place. Using the improved tuning technique for the deadbeat, Dahlin and the Smith predictor algorithms, this difficulty has been overcome since the improved tuning procedure is essentially to force the controller to calculate a stronger and more rapid control action by using a transfer function model, in the design procedure, which is less sensitive and has slower dynamics than the actual process.

The simulation results showed that the response of the controlled variable (bottom composition) in the tests of the deadbeat, Dahlin and Smith predictor algorithms for both regulatory (after the use of the improved tuning procedure) and servo control were quite smooth. However, the response of the manipulated variable (steam flow) using the deadbeat algorithm might not be acceptable for industrial application (cf. Figure 5.3.6, where the steam flow exhibits more than 100% overshoot). For the Dahlin algorithm and the Smith predictor, this problem can be avoid by adjusting the tuning constants in these algorithms to obtain an acceptable response of the manipulated variable without causing a serious

deterioration in the control performance (cf. Figures 5.4.13 and 5.4.14).

Although the response of the controlled and manipulated variables are quite sluggish and oscillatory when composition is controlled with the PI and PID algorithms for time delay processes, these algorithms do have the advantage that they are model independent and so are easier to implement for any control system.

6. Experimental Implementation and Evaluation

6.1 Introduction

The objectives of the experimental work of this project were somewhat different from those of the digital simulation study outlined in Chapter 5. In the experimental work, efforts were directed to

1) implementation of the different control algorithms using the process control software system DISCO (5,62,63,64,65);
2) evaluation of the control performance of the different algorithms for a -25% step change in feed flow rate; and
3) on-line tuning techniques for the different control algorithms, particularly the tuning technique for the Dahlin algorithm.

In the evaluation of the performance of the different control algorithms, the deadbeat algorithm was not considered, primarily because the algorithm did not have any provision for tuning parameters to adjust different operating conditions (cf. Section 3.4).

In the next section, Section 6.2, the description of the pilot scale distillation column unit used in this project is presented. An outline of the basic operation of the DISCO system is given in Section 6.3. The control performance results for the different algorithms under regulatory and servo control operation are presented in Sections 6.4

and 6.5 respectively. The on-line tuning techniques used in the experimental evaluation of the different control algorithms are given in Section 6.6 and the discussion of experimental results is presented in Section 6.7.

6.2 Description of the Distillation Column Unit

The experimental evaluation of the different control algorithms was conducted on the pilot scale binary distillation column located in the Department of Chemical Engineering. The column originally designed and fabricated by Svrcek (55) has been used for various types of control studies during the last few years. The column is 22.9 cm in diameter and has eight bubble cap trays on a 30.5 cm spacing. Each tray contains four bubble caps. The column is also equipped with a total condenser and a thermosyphon reboiler. The liquid levels in the condenser and the reboiler are controlled by manipulating the top and bottom product flows respectively using local analog PI controllers. The column is maintained at approximately atmospheric pressure by adjusting the cooling water flow through the condenser. The feed flow is pumped to the column at the fourth tray after passing through a preheater for maintaining constant feed enthalpy. Similarly, the reflux is also preheated to maintain constant reflux enthalpy before it is returned to the column at the eighth tray. A schematic diagram of the distillation column unit is shown in Figure 6.2.1 and the typical operating conditions used during the experimental

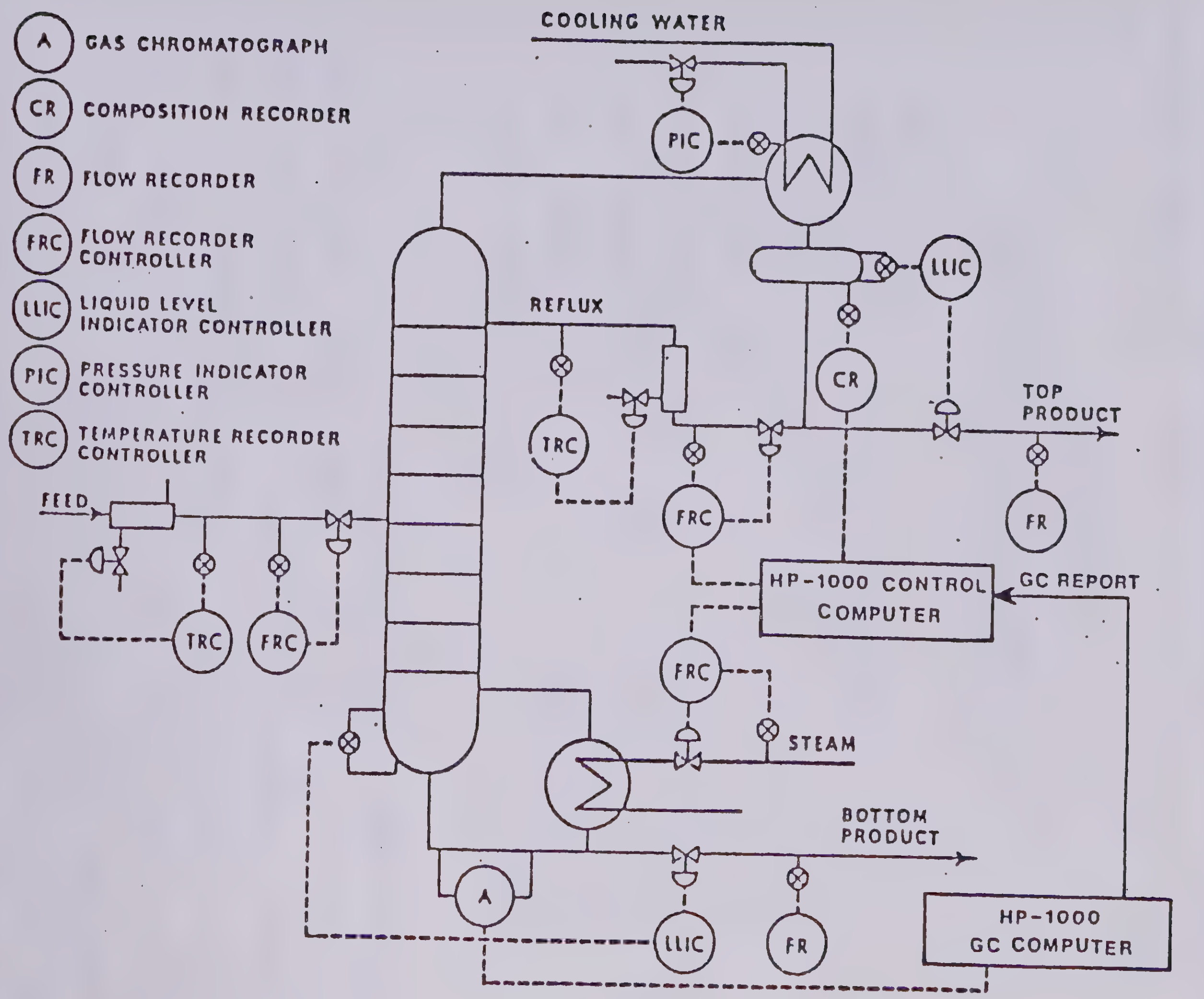

A
GAS CHROMATOGRAPH
CR
COMPOSITION RECORDER
FR
FLOW RECORDER
FRC
FLOW RECORDER CONTROLLER
LLIC
LIQUID LEVEL INDICATOR CONTROLLER
PIC
PRESSURE INDICATOR CONTROLLER
TRC
TEMPERATURE RECORDER CONTROLLER
COOLING WATER
PIC
LLIC
REFLUX
TRC
CR
TOP PRODUCT
FRC
FR
FEED
TRC
FRC
HP-1000 CONTROL COMPUTER
GC REPORT
FRC
STEAM
BOTTOM PRODUCT
A
LLIC
FR
HP-1000 GC COMPUTER

Figure 6.2.1 Schematic Diagram of the Pilot Scale Distillation Column Unit

runs are listed in Table 6.2.1. Specific details regarding the design of the binary distillation column unit are given by Svrcek (55).

Table 6.2 1

Steady State Operating Conditions of the Binary Distillation Column Unit

Feed Flow Rate	18.0 g/s
Bottom Product Flow Rate	9.0 g/s
Top Product Flow Rate	9.0 g/s
Reflux Flow Rate	9.6 g/s
Steam Flow Rate	14.0 g/s
Feed Composition	50.4 wt.% MeOH
Top Composition	95.3 wt.% MeOH
Bottom Composition	5.0 wt.% MeOH

In order to provide data acquisition and implementation of the different control schemes, the distillation column is interfaced with the distributed HP 1000 computer system. A HP 5720 gas chromatograph which is also interfaced with the HP 1000 computer system, is used for direct measurement of the bottom product composition. During each experimental run, eight key variables, namely feed flow rate, bottom flow rate, top product flow rate, reflux flow rate, steam flow rate, condensate level, top product composition and bottom product composition, were recorded on disc using DISCO. These variables plus the column pressure were monitored every 3 minutes by a safety monitor program. For implement-

ation of the control scheme, only the manipulated variables, steam and reflux flow rates, were under a supervisory type of control with the outputs of the control calculations being used as the setpoints for the local analog PI controllers while the other variables were under local analog PI control.

6.3 Implementation of Control Algorithms using DISCO

The operation of DISCO is based on the concept of table-driven processing. One of the distinct features of DISCO is its flexible data base structure. Each activity (or loop) of DISCO is built by adding different segments which perform different tasks, to the activity header which identifies itself from other activities. The operation within an activity is task-driven, i.e. different segment processors (or FORTRAN subroutines) will be called by the DISCO main program to process the data base of a particular activity. For a single input-single output feedback control loop, the simplest structure of an activity contains an activity header; an input segment which acquires the measurement of the controlled variable; a control segment which performs the control calculation according to the control algorithm chosen; and an output segment which sends the calculated value of the manipulated variable to the process. A description of the organization and operation of DISCO is given by Brennek (5) and in documentation available from the DACS Center (62,

63,64,65). A list of the activities used in this work is available from the DACS Centre.

During the project, the existing input and output segment processors (5) were rewritten to allow for greater flexibility for the users. A control segment processor which can perform the control calculation using Equation 3.1.1, was written to allow for the implementation of different control algorithms using the same activity. A special segment processor, the program scheduler, was also written for actuating the gas chromatograph operation or data acquisition. The program coding and the user's manuals for these segment processors are available from the DACS Center (62, 63,64 65).

A set of interactive programs which can be used to directly access the data base of an activity were written to provide for implementation of on-line control algorithm tuning. These programs are available from the DACS Centre.

6.4 Performance of the Algorithms for Regulatory Control

Since the distillation column is a highly nonlinear system, especially the response of bottom product composition to step changes in feed flow rate, it is necessary for a control algorithm to use different sets of tuning constants for controlling different disturbances in order to yield optimal performance. In the experimental evaluation, the performance of the different algorithms for a -25% step change in feed flow rate is of particular interest since

this change is the most severe disturbance for the pilot scale distillation column. Summaries of the performance of the different control algorithms, namely the digital PI and PID control algorithm, the Dahlin and Smith predictor control algorithms, are given in Table 6.4.1 and 6.4.2. The bottom composition control responses using the above algorithms are shown in Figures 6.4.1 to 6.4 8.

6.5 Discussion of Regulatory Control Results

Using the IAE value as the performance criterion, it was found from the experimental evaluation of the different control algorithms for a -25% step change in feed flow rate that the Smith predictor provided the best performance as indicated by its lowest IAE values (cf. Table 6.4.1). However the controlled behaviour achieved using the Dahlin algorithm was virtually equivalent as indicated by its IAE values (cf. Table 6.4.1). Tests using the digital PID algorithm showed that by careful tuning, its performance was comparable to that achieved using the Smith predictor and the Dahlin algorithms. The performance of the digital PI algorithm was inferior to that of the other algorithms, as indicated by its highest IAE values (cf. Table 6.4.1).

Although the Dahlin algorithm is not specifically a time delay compensation control scheme such as the Smith predictor scheme, which cancels the time delay term in the system characteristic equation, its successful performance compared to the performance of the digital PI algorithm

Table 6.4.1

Summary of Experimental Results for Control of Bottom Composition for a -25% Step Change in Feed Flow Rate

Algorithm	K_C	K_I	K_D	K_p	T_p	T_d	IAE	Figure
PI	-0.607	-0.095	—	—	—	—	5148	6 4.1
PID	-0.523	-0.117	-0.200	—	—	—	4477	6.4.2
Dahlin	λ=164s	—	—	-3.14	918	187	4253	6.4.3
Smith Pred.	-0.747	-0.213	—	-2.70	872	187	4236	6.4.4

K_C = (g/s)/wt.%

K_I = (g/s)/(wt.%-s)

K_D = (g/s)/(wt.%/s)

IAE = wt.%-s

K_p = wt.%/(g/s)

T_p = s

T_d = s

Table 6.4.2

Summary of Experimental Results for Control of Bottom Composition for a +25% Step Change in Feed Flow Rate

Algorithm	K_C	K_I	K_D	K_p	T_p	T_d	IAE	Figure
PI	-0.551	-0.122	—	—	—	—	4014	6.4.5
PID	-0.503	-0.125	-0.075	—	—	—	4158	6.4.6
Dahlin	λ=231s	—	—	-3.14	918	187	5022	6.4.7
Smith Pred.	-0.711	-0.185	—	-2.70	872	187	4662	6.4.8

K_C = (g/s)/wt.%

K_I = (g/s)/(wt.%-s)

K_D = (g/s)/(wt.%/s)

IAE = wt.%-s

K_p = wt.%/(g/s)

T_p = s

T_d = s

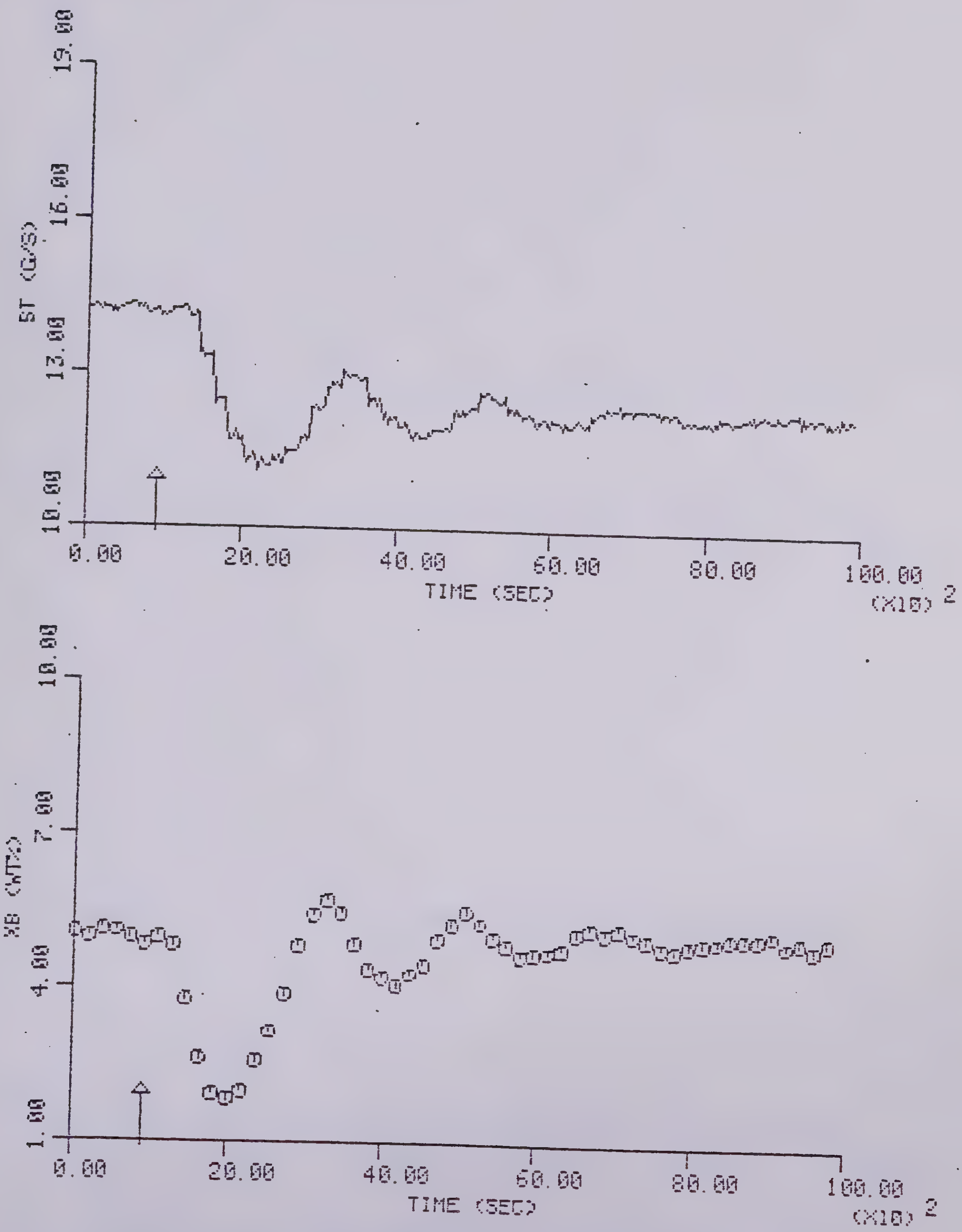


Figure 6.4.1 PI Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (Run E-PI24; $K_C = -0.607$, $K_I = -0.095$)

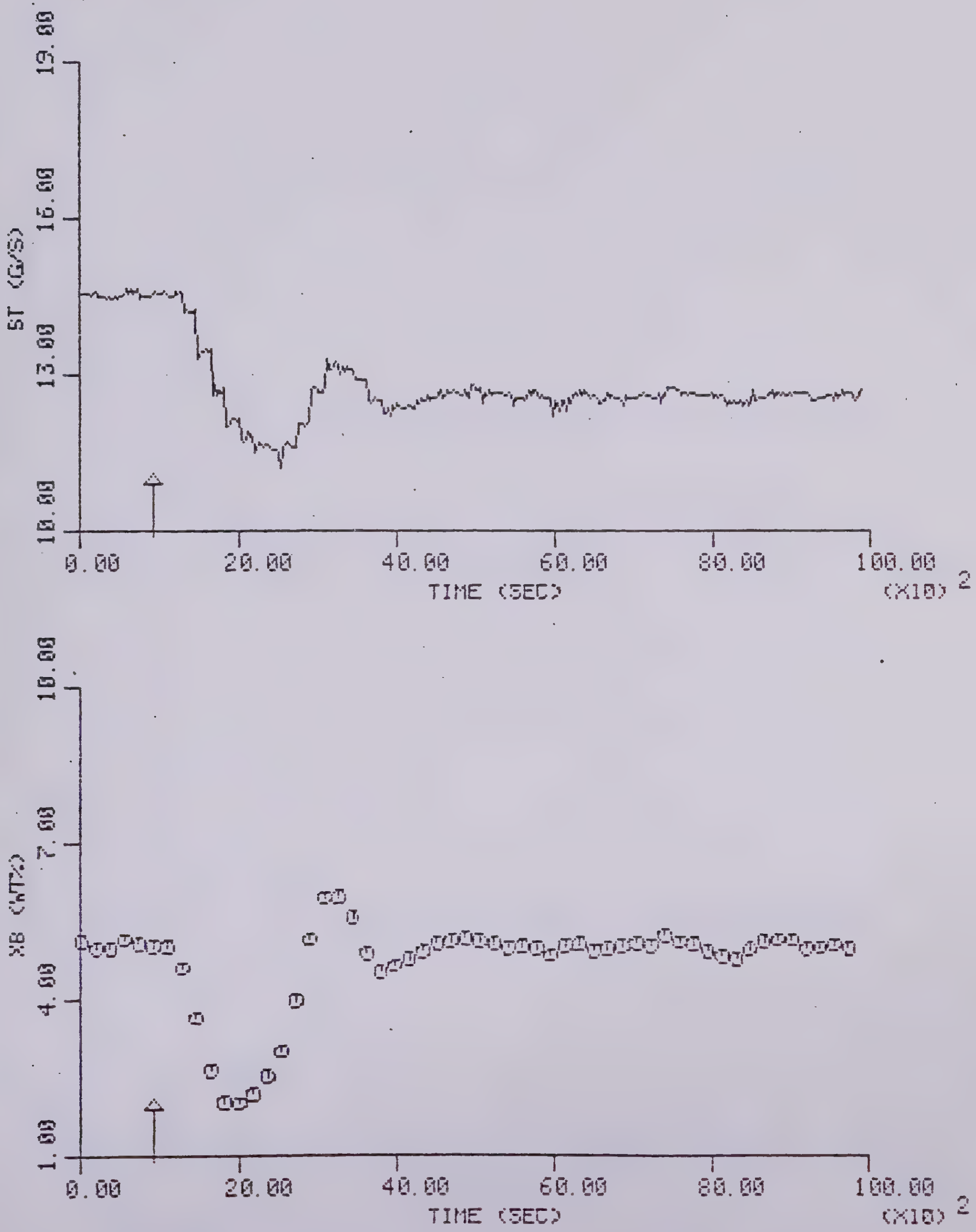


Figure 6.4.2 PID Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (Run E-PID21; K_C= -0.523, K_I= -0.117, K_D= -0.200)

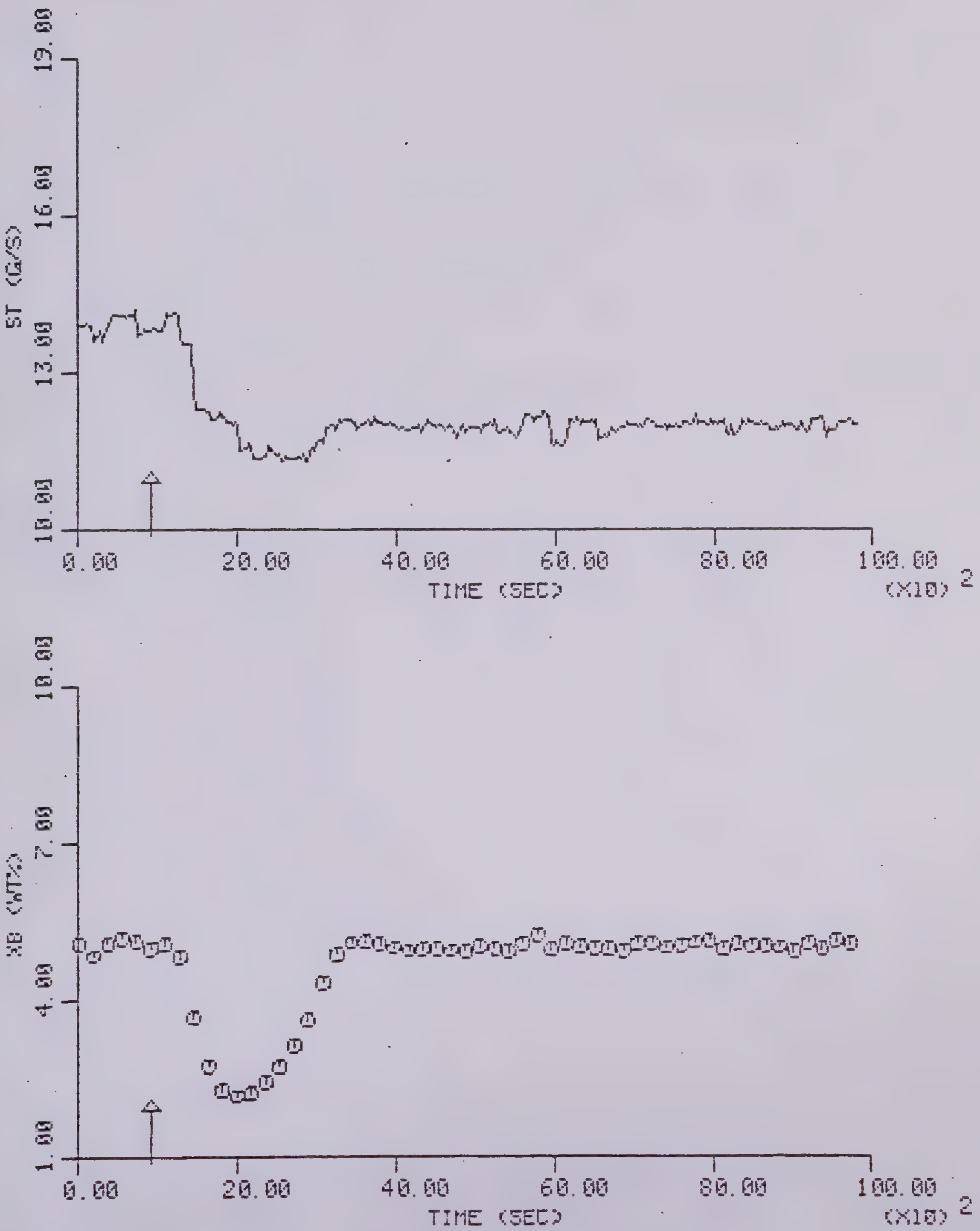


Figure 6.4.3 Dahlin Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-DAH13; $K_p = -3.14$, $T_p = 918.0$, $T_d = 187.0$, $\lambda = 164.0$)

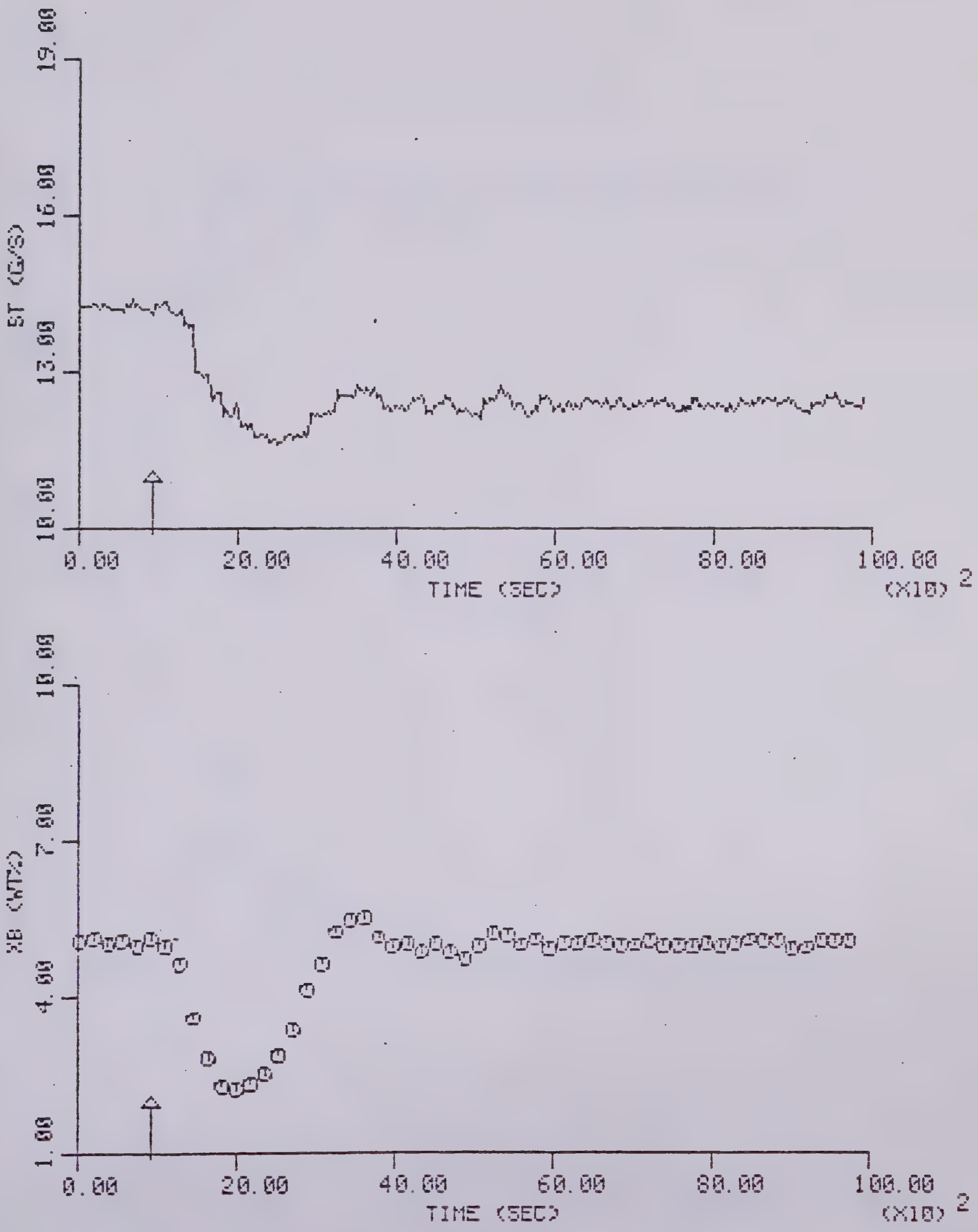


Figure 6.4.4 Smith Predictor Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-SLP23; $K_p = -2.70$, $T_p = 872.0$, $T_d = 187.0$, $K_C = -0.747$, $K_I = -0.213$)

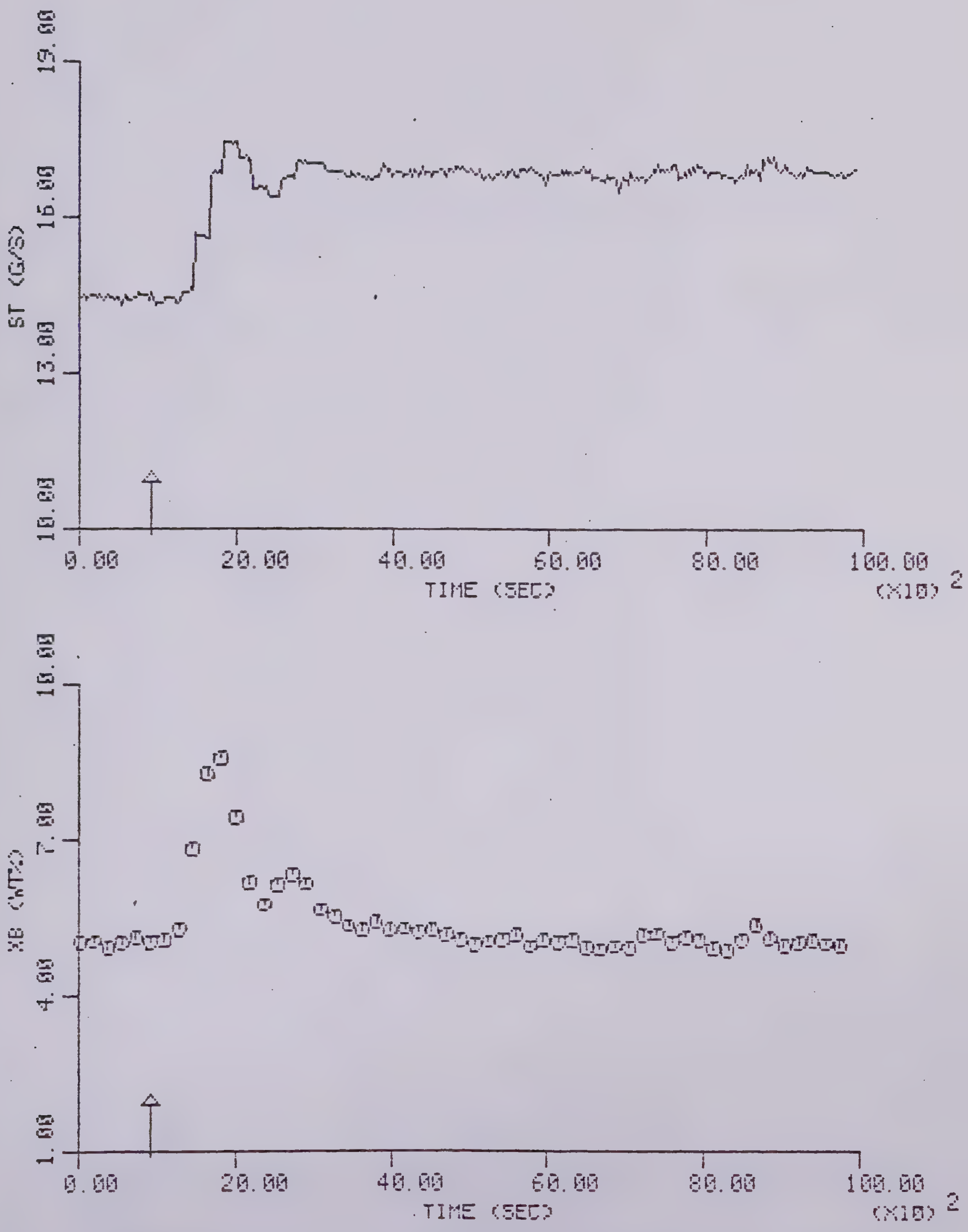


Figure 6.4.5 PI Algorithm Control of Bottom Composition for a +25% Step Change in Feed Flow Rate (Run E-PI16; $K_C = -0.551$, $K_I = -0.122$)

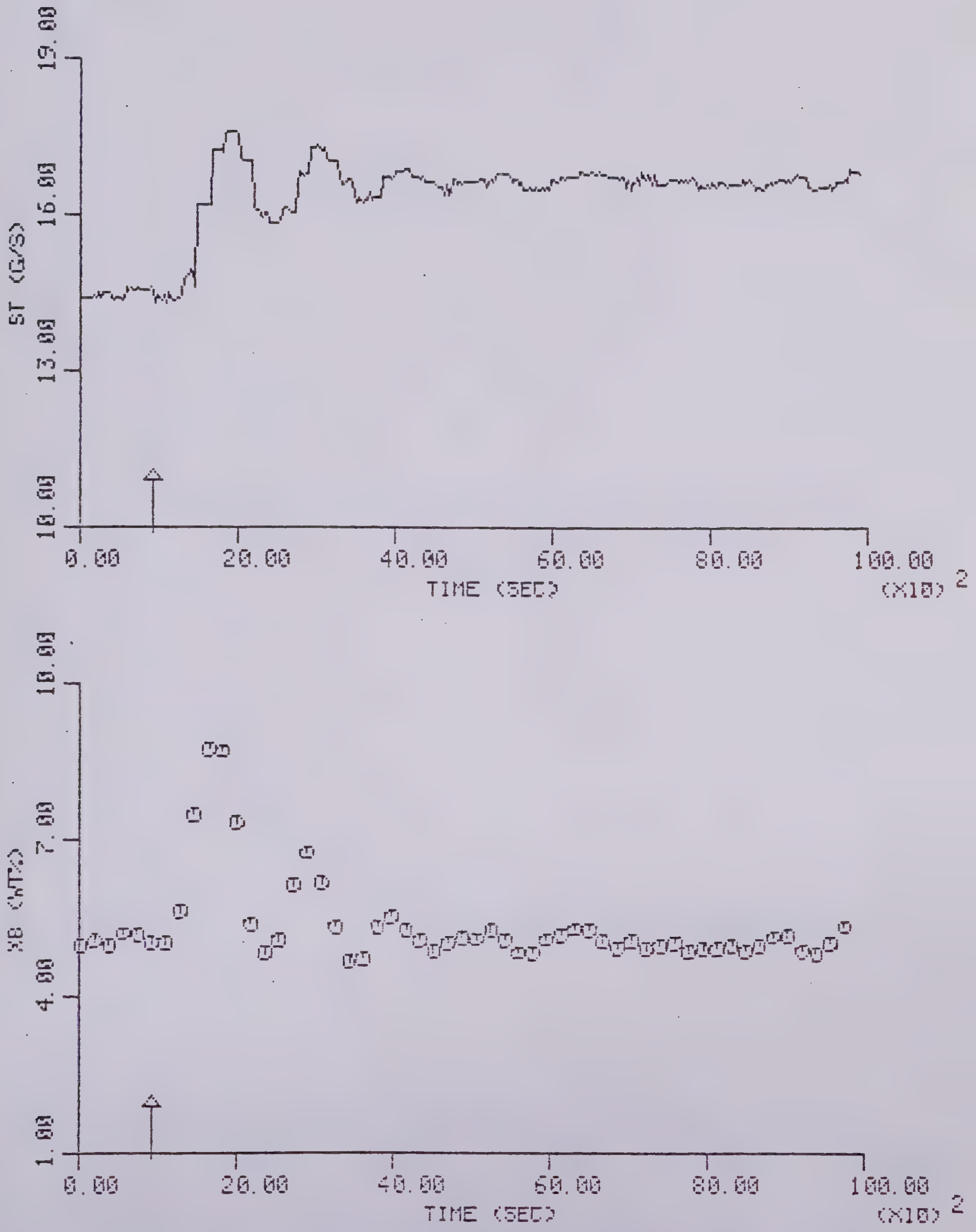


Figure 6.4.6 PID Algorithm Control of Bottom Composition for a +25% Step Change in Feed Flow Rate (Run E-PID23; $K_C = -0.503$, $K_I = -0.125$, $K_D = -0.075$)

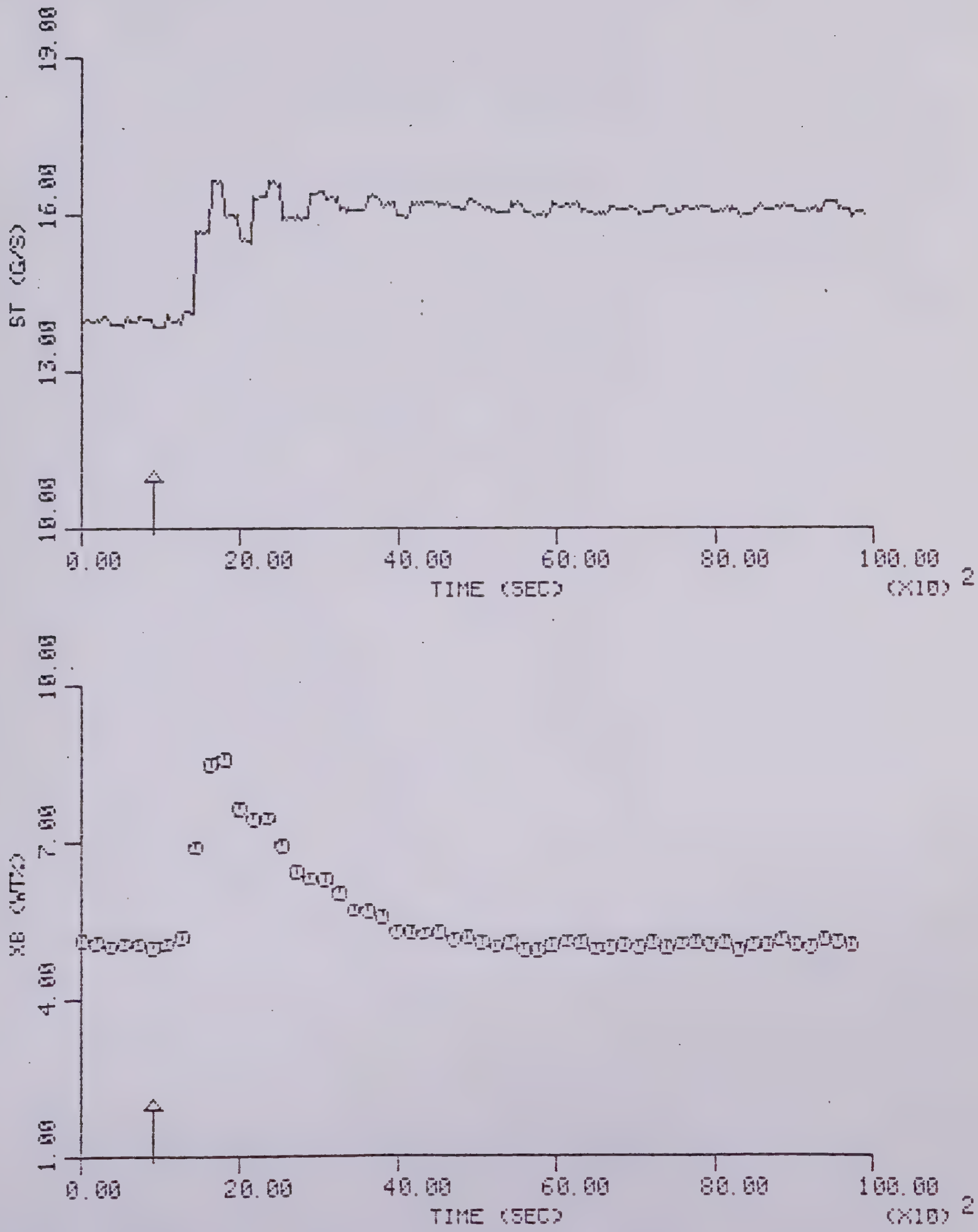


Figure 6.4.7 Dahlin Algorithm Control of Bottom Composition for +25% Step Change in Feed Flow Rate (Run E-DAH26; $K_p = -3.14$, $T_p = 918.0$, $T_d = 187.0$, $\lambda^P = 231.0$)

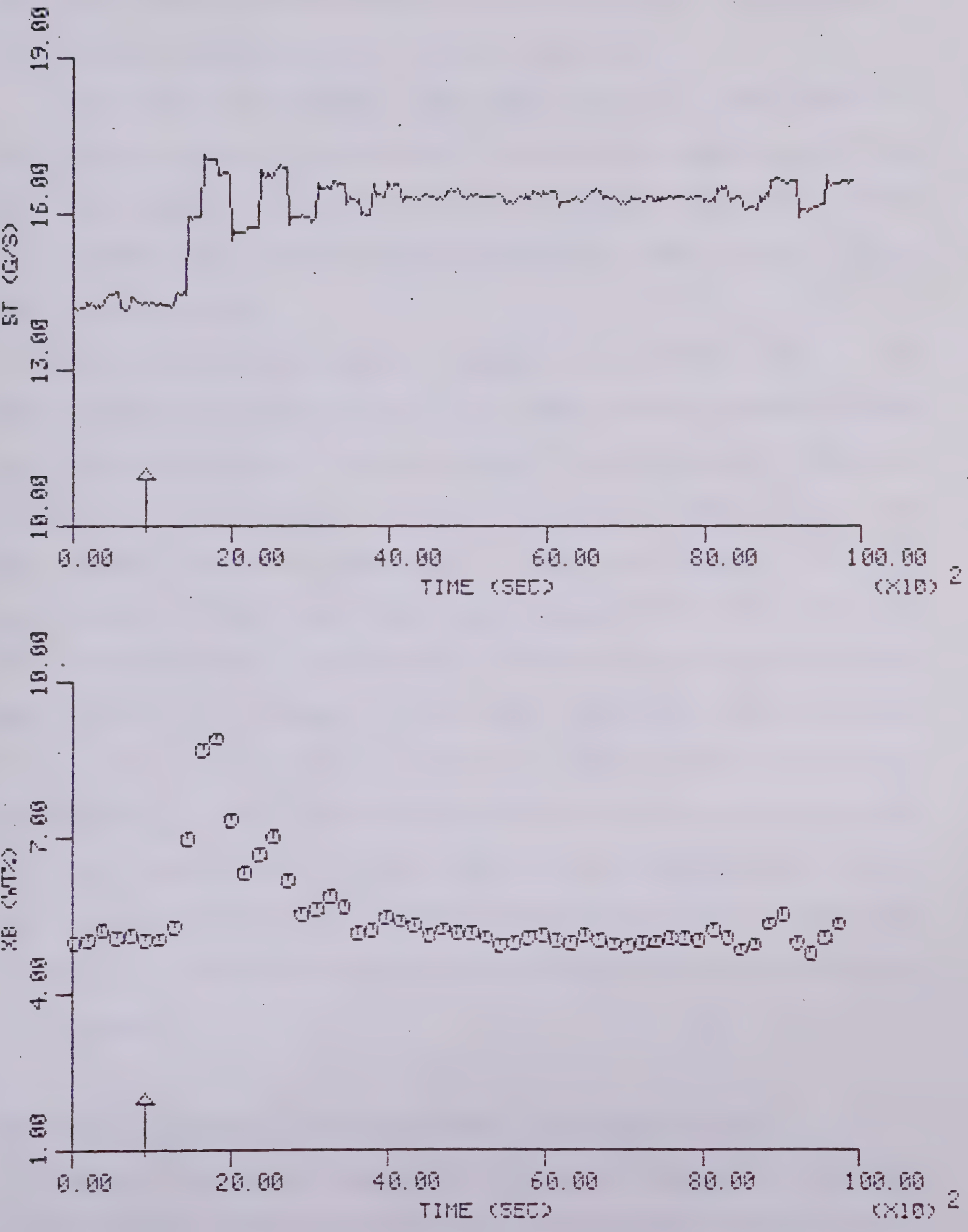


Figure 6.4.8 Smith Predictor Control of Bottom Composition for +25% Step Change in Feed Flow Rate (Run E-SLP22; $K_p = -2.70$, $T_p = 872.0$, $T_d = 187.0$, $K_C = -0.711$, $K_I = -0.185$)

results from the consideration of the process characteristics during the controller design procedure.

For the PID control algorithm, properly tuned derivative action definitely provided significant compensation for the time delay as indicated by the much lower IAE values (cf. Table 6.4.1) than those resulting from control using the PI algorithm.

In the case of bottom composition control for a +25% step change in feed flow rate, the control performance using the Smith predictor, Dahlin and PID algorithms was inferior to that achieved using the PI algorithm as indicated by the IAE values shown in Table 6.4.2. Some explanation for this performance is the fact that these algorithms were not tuned for this particular disturbance. A further contributing factor to this performance is the fact that when the feed flow rate is increased, the distillation column operates close to the flooding region so the assumed transfer function models for the distillation column dynamics are probably not reliable. Consequently, the control performance for an increase in feed flow rate do not provide a valid evaluation of these algorithms.

6.6 Performance of the Algorithms for Servo Control

Since load disturbances occur more frequently than set point changes, most of the controllers in the process industries are tuned for regulatory control. From this point of view, it was more practical to investigate the performance

of the different control algorithms for servo control using the tuning constants used for regulatory control than to tune the algorithms strictly for servo control operation. In this work, the tuning constants used for composition control with the column subjected to a -25% step change in feed flow rate were also used in the algorithms for controlling the bottom composition for ±1% changes in set point. The IAE values for the performance of the different algorithms are given in Tables 6.5.1 and 6.5.2. The composition responses using the different control algorithms are given in Figures 6.5.1 to 6.5.8.

6.7 Discussion of Servo Control Results

From the results shown in Tables 6.5.1 and 6.5.2, it can be seen that the Dahlin algorithm with the same tuning constants as used for regulatory control for a -25% step change in feed flow rate, provided the best and the most consistent performance for both ±1% step changes in set point. The overall performance of the Smith predictor was close to that of the Dahlin algorithm particularly for the -1% step change in set point which gave an IAE value nearly equal to that achieved using the Dahlin algorithm. Control performance using the PI and PID algorithms with constants determined for a -25% step disturbance in feed flow rate was inferior to that achieved using the Dahlin algorithm or Smith predictor. This is indicated not only by the higher IAE value (cf. Tables 6.5.1 and 6.5 2), but by the composi-

Table 6.5 1

Summary of Experimental Results for Control of Bottom Composition for a -1% Step Change in Set Point

Algorithm	K_C	K_I	K_D	K_p	T_p	T_d	IAE	Figure
PI	-0.607	-0.095	—	—	—	—	1249	6.5 1
PID	-0.523	-0 117	-0.200	—	—	—	947	6.5.2
Dahlin	λ=164s	—	—	-3 14	918	187	835	6.5.3
Smith Pred.	-0.869	-0.209	—	-3.14	918	187	837	6.5.4

K_C = (g/s)/wt.%

K_I = (g/s)/(wt.%-s)

K_D = (g/s)/(wt.%/s)

IAE = wt.%-s

K_p = wt.%/(g/s)

T_p = s

T_d = s

Table 6.5.2

Summary of Experimental Results for Control of Bottom Composition for a +1% Step Change in Set Point

Algorithm	K_C	K_I	K_D	K_p	T_p	T_d	IAE	Figure
PI	-0.607	-0.095	—	—	—	—	1580	6.5.5
PID	-0.523	-0.117	-0.200	—	—	—	1159	6.5.6
Dahlin	λ=164s	—	—	-3 14	918	187	956	6.5.7
Smith Pred.	-0.869	-0.209	—	-3.14	918	187	1107	6.5.8

K_C = (g/s)/wt.%

K_I = (g/s)/(wt.%-s)

K_D = (g/s)/(wt.%/s)

IAE = wt.%-s

K_p = wt.%/(g/s)

T_p = s

T_d = s

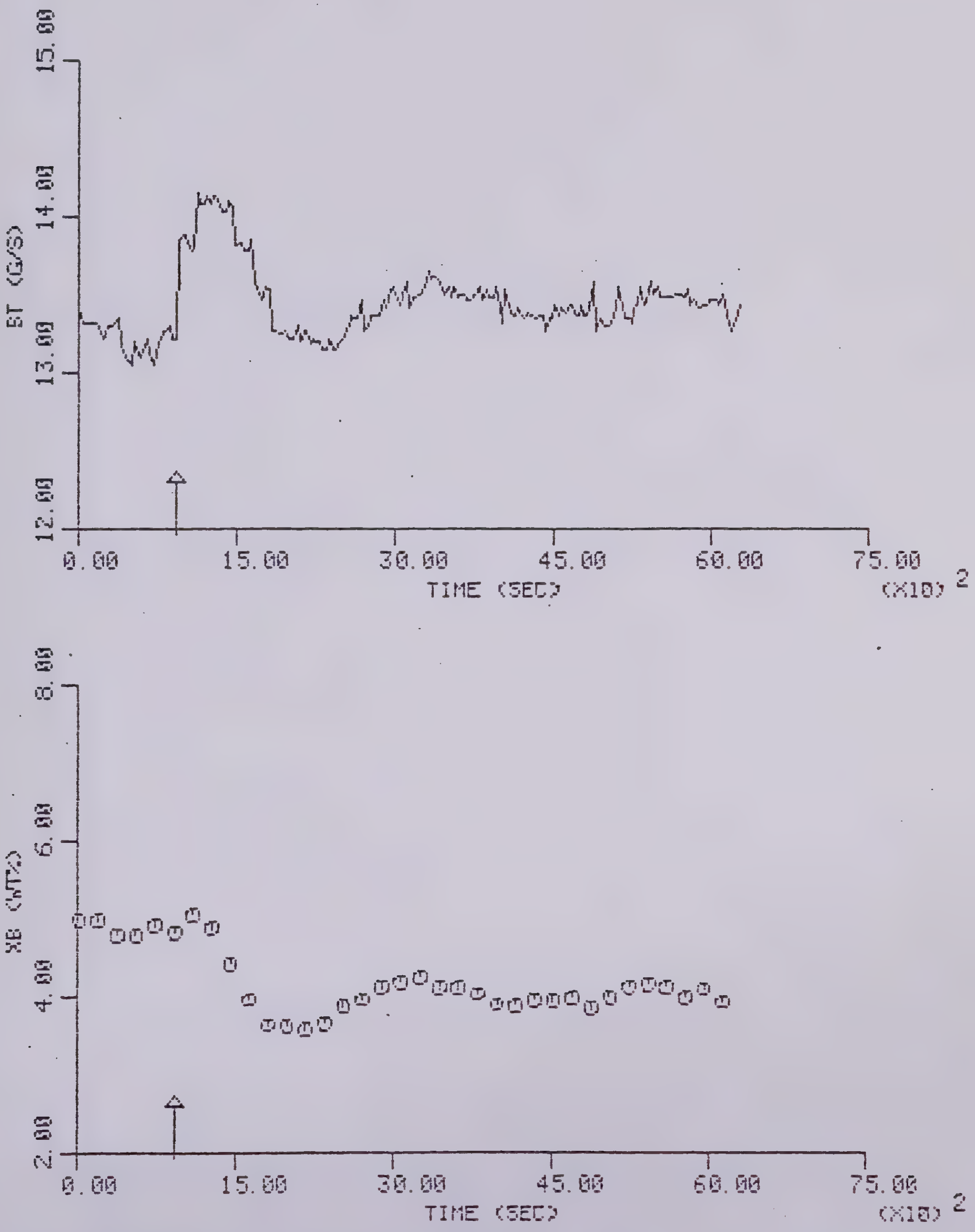


Figure 6.5.1 PI Algorithm Control of Bottom Composition for a -1% Step Change in Set Point (Run E-PI29; K_C = -0.607, K_I = -0.095)

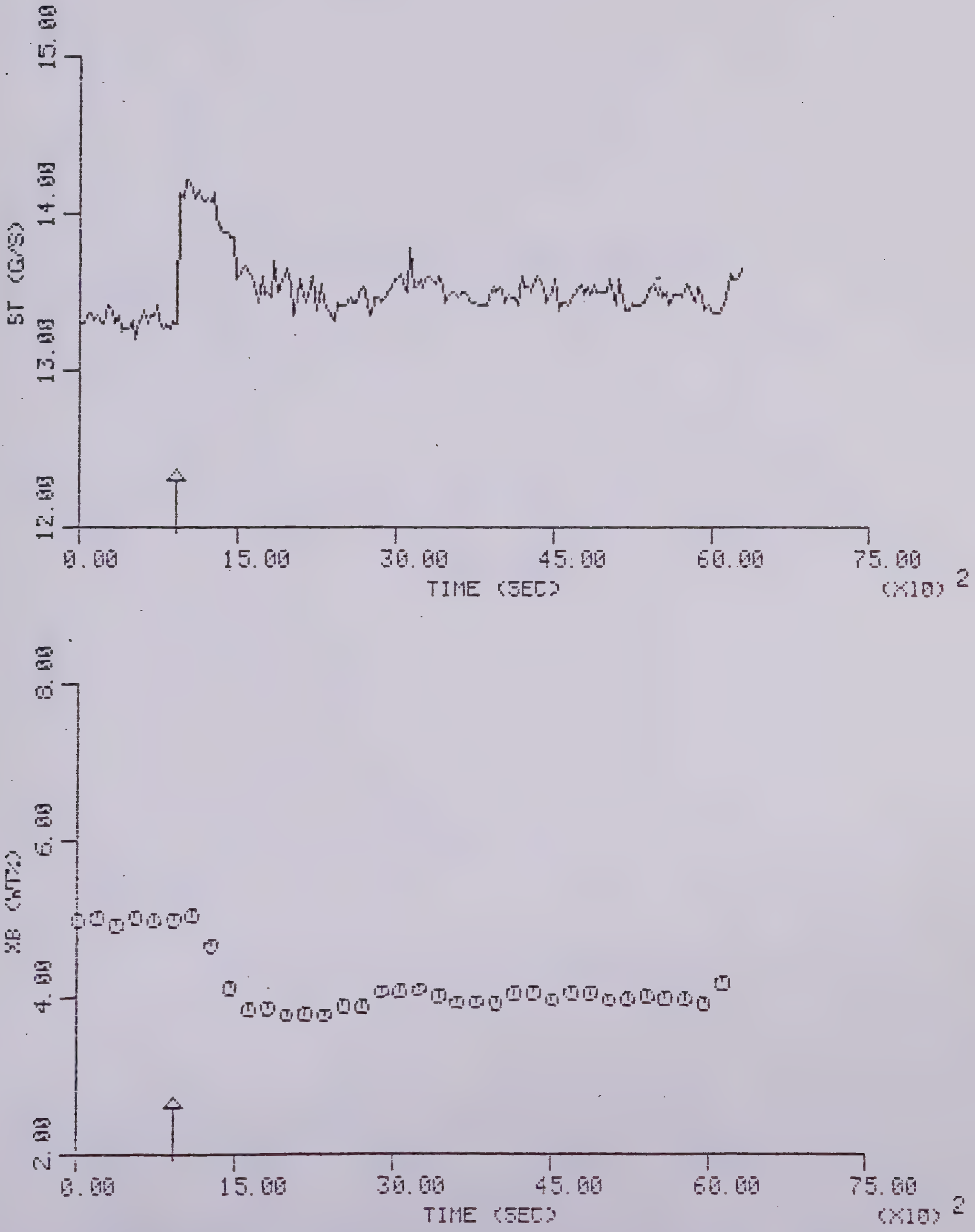


Figure 6.5.2 PID Algorithm Control of Bottom Composition for a -1% Step Change in Set Point (Run E-PID27; $K_C = -0.523$, $K_I = -0.117$, $K_D = -0.200$)

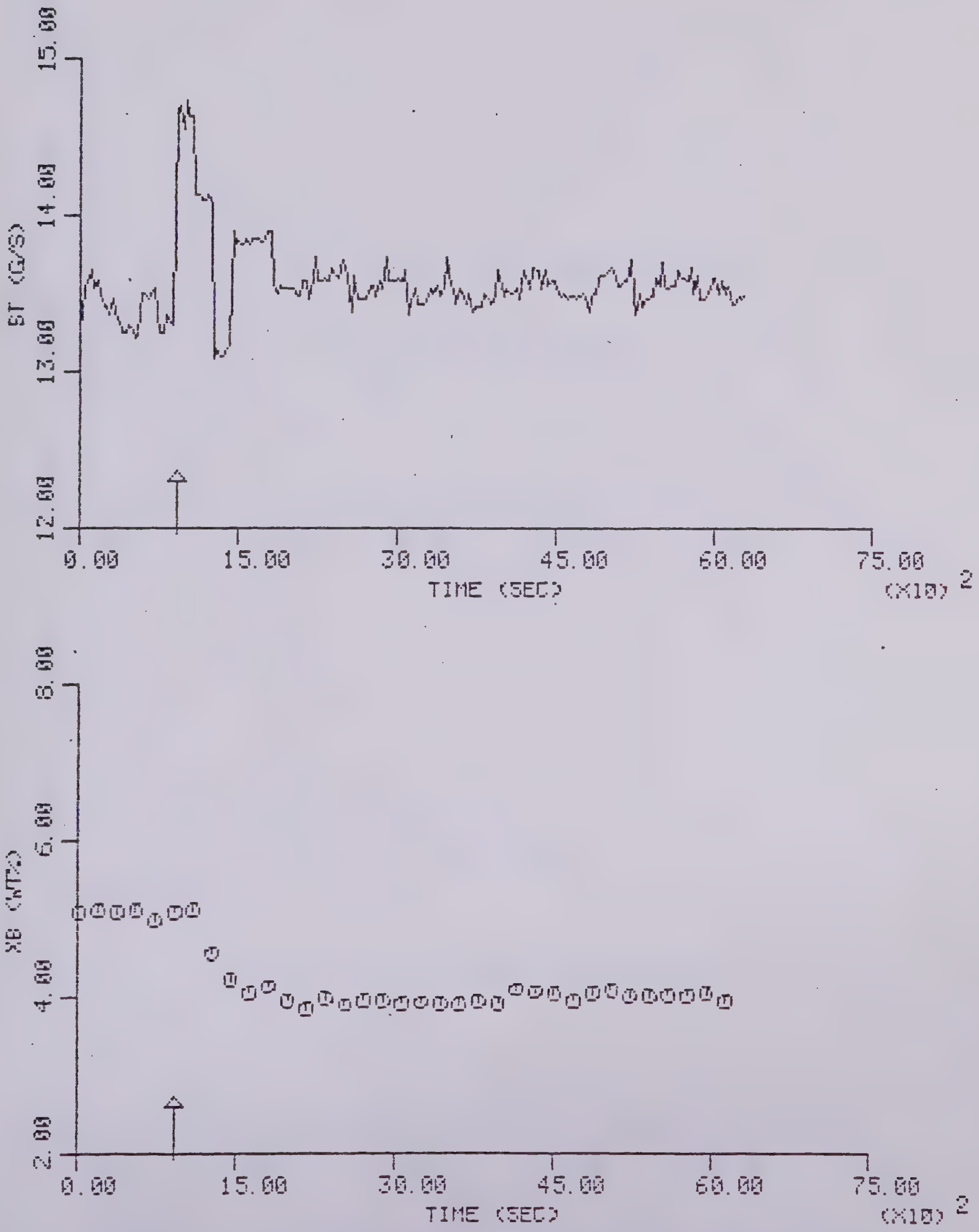


Figure 6.5.3 Dahlin Algorithm Control of Bottom Composition for -1% Step Change in Set Point (Run E-DAH28; K_p = -3.14, T_p = 918.0, T_d = 187.0, λ = 164.0)

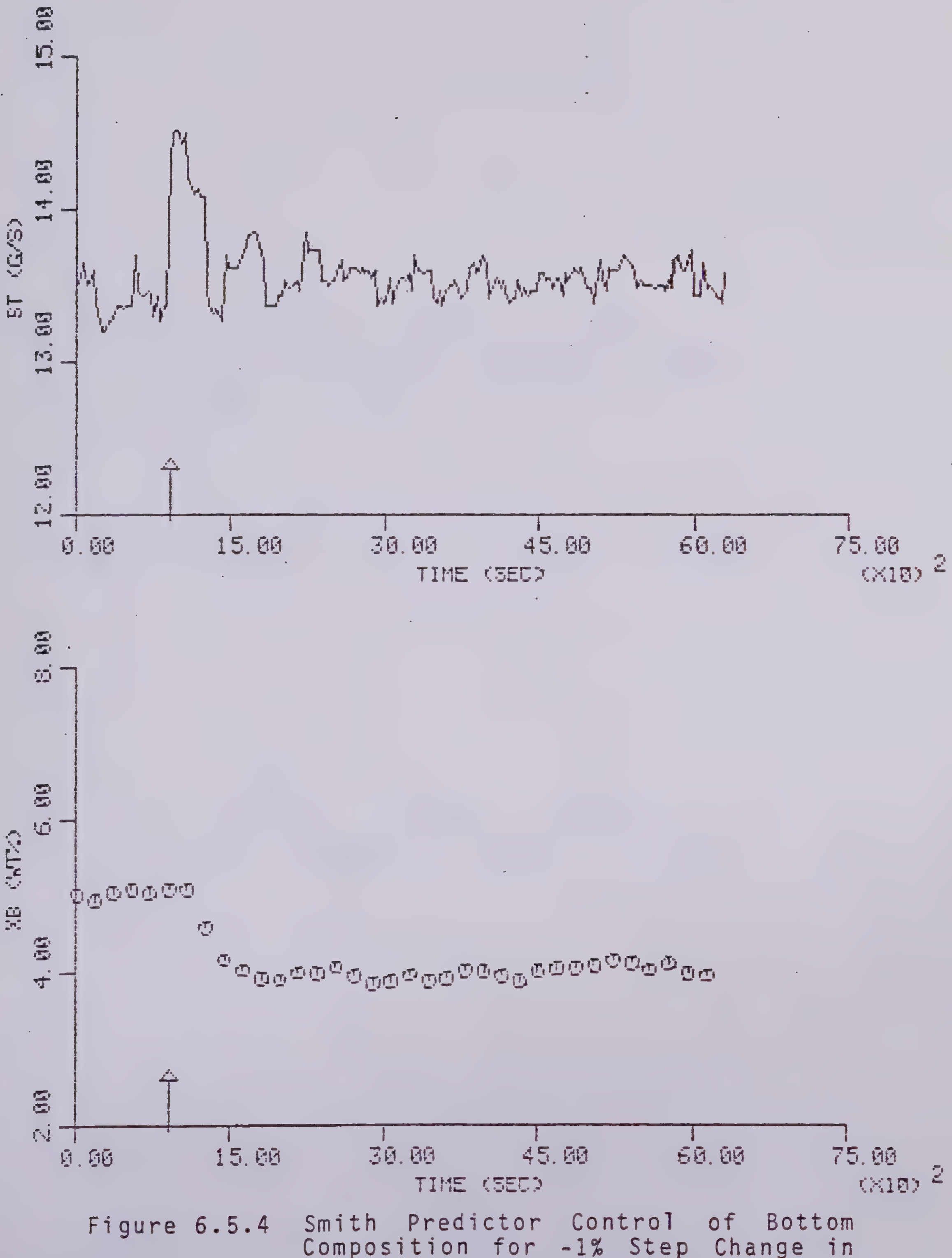


Figure 6.5.4 Smith Predictor Control of Bottom Composition for -1% Step Change in Set Point (Run E-SLP32; $K_p = -3.14$, $T_p = 918.0$, $T_d = 187.0$, $K_C = -0.869$, $K_I = -0.209$)

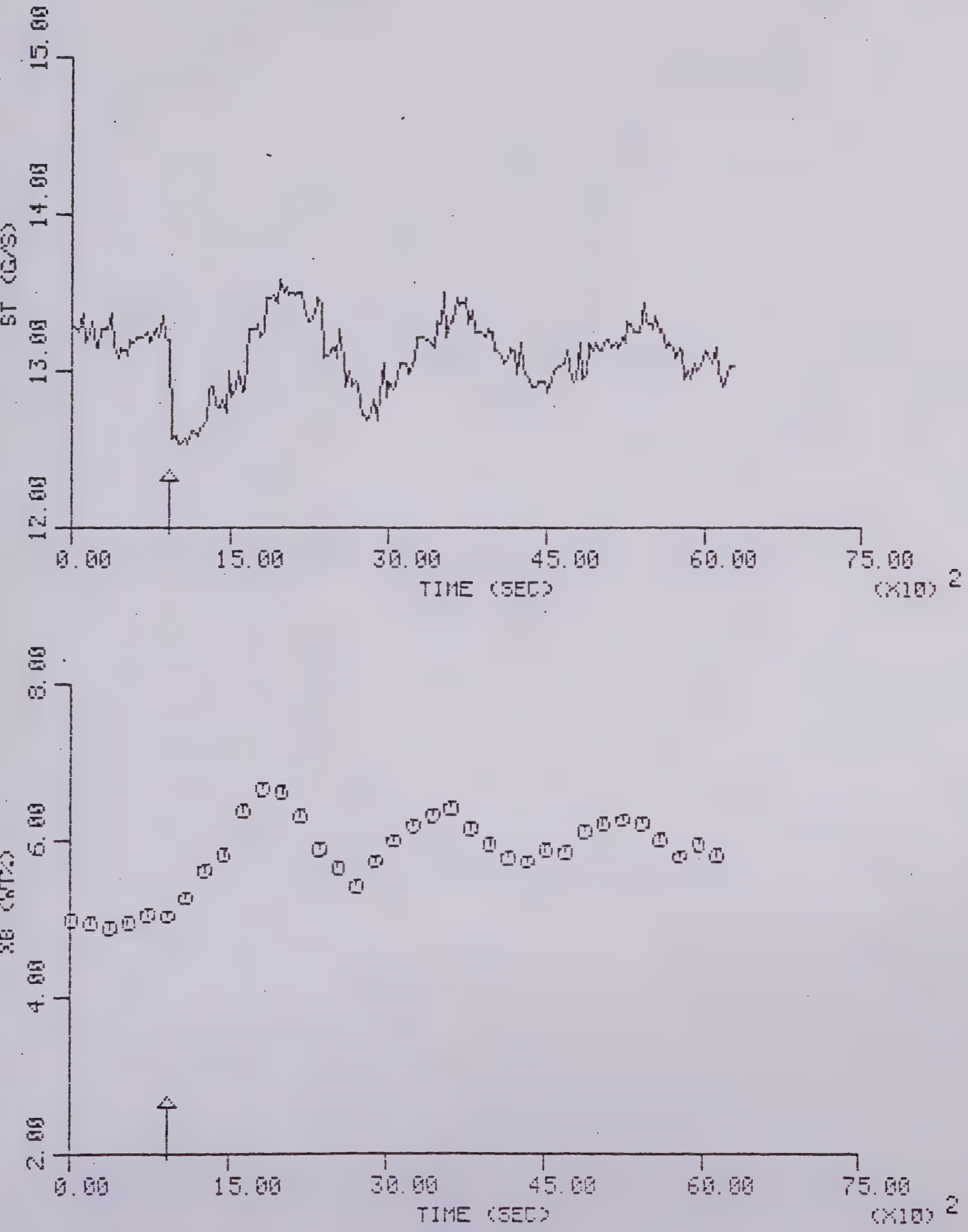


Figure 6.5.5 PI Algorithm Control of Bottom Composition for a +1% Step Change in Set Point (Run E-PI31; K_C = -0.607, K_I = -0.095)

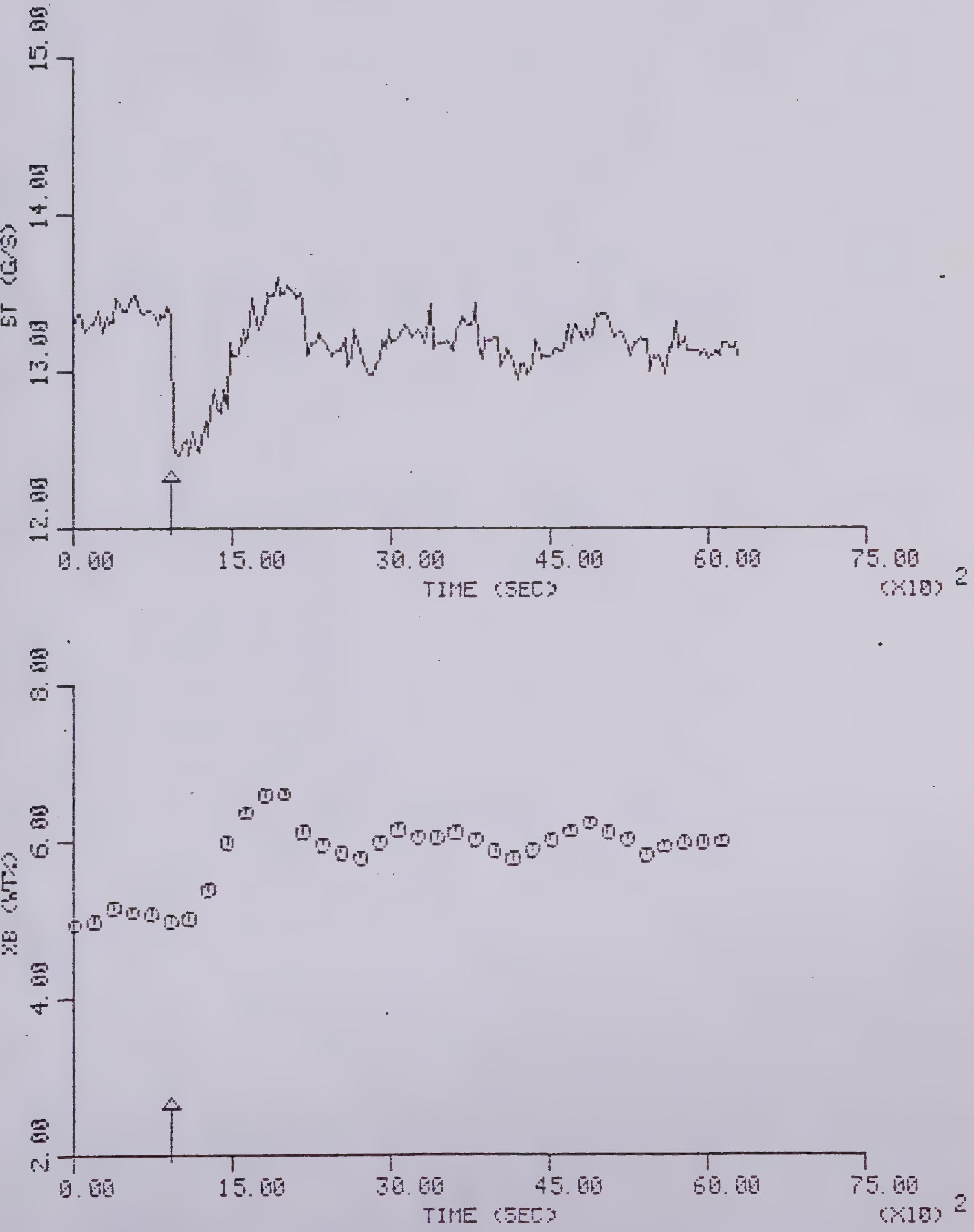


Figure 6.5.6 PID Algorithm Control of Bottom Composition for a +1% Step Change in Set Point (Run E-PID29; $K_C = -0.523$, $K_I = -0.117$, $K_D = -0.200$)

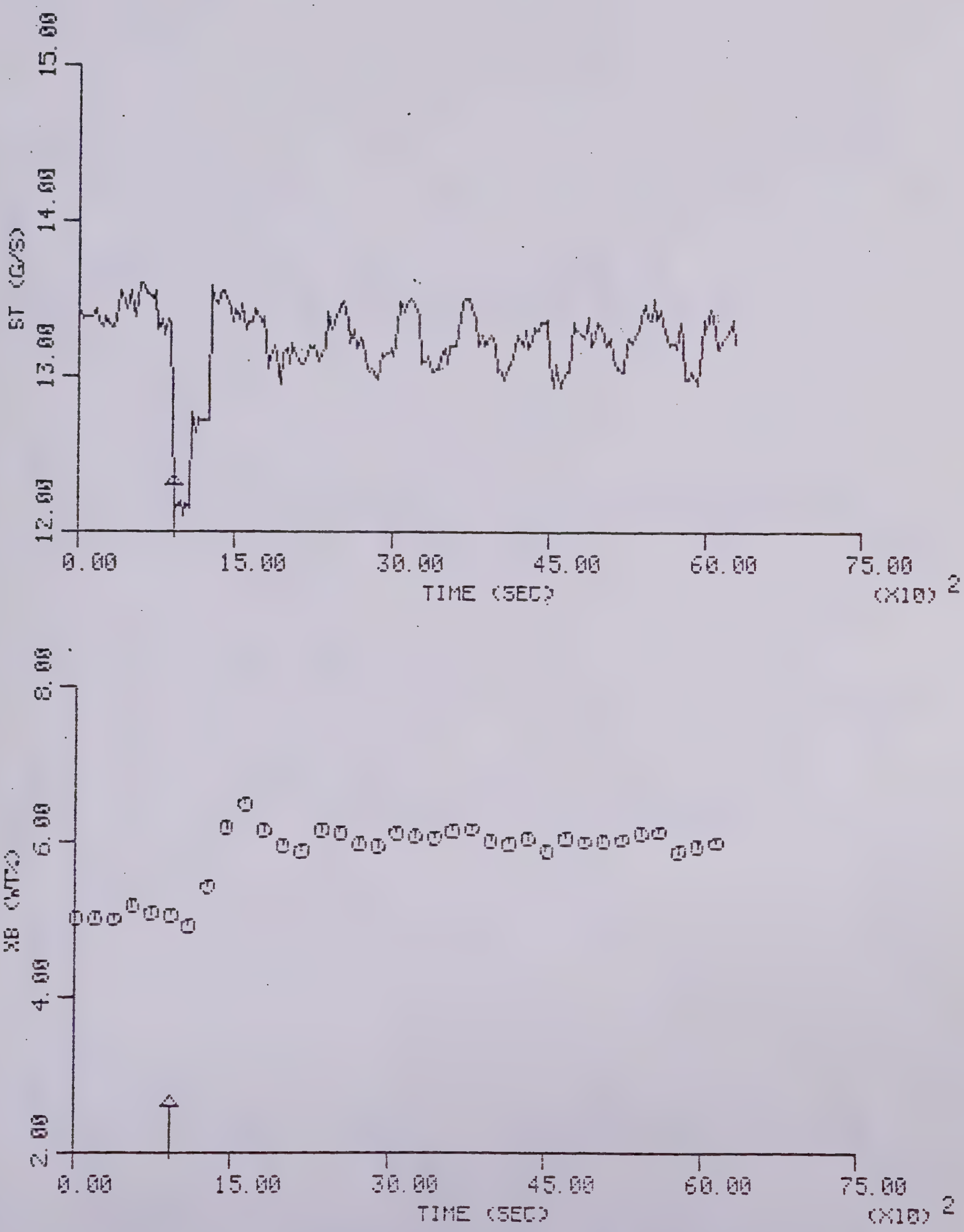


Figure 6.5.7 Dahlin Algorithm Control of Bottom Composition for +1% Step Change in Set Point (Run E-DAH30; $K_p = -3.14$, $T_p = 918.0$, $T_d = 187.0$, $\lambda = 164.0$)

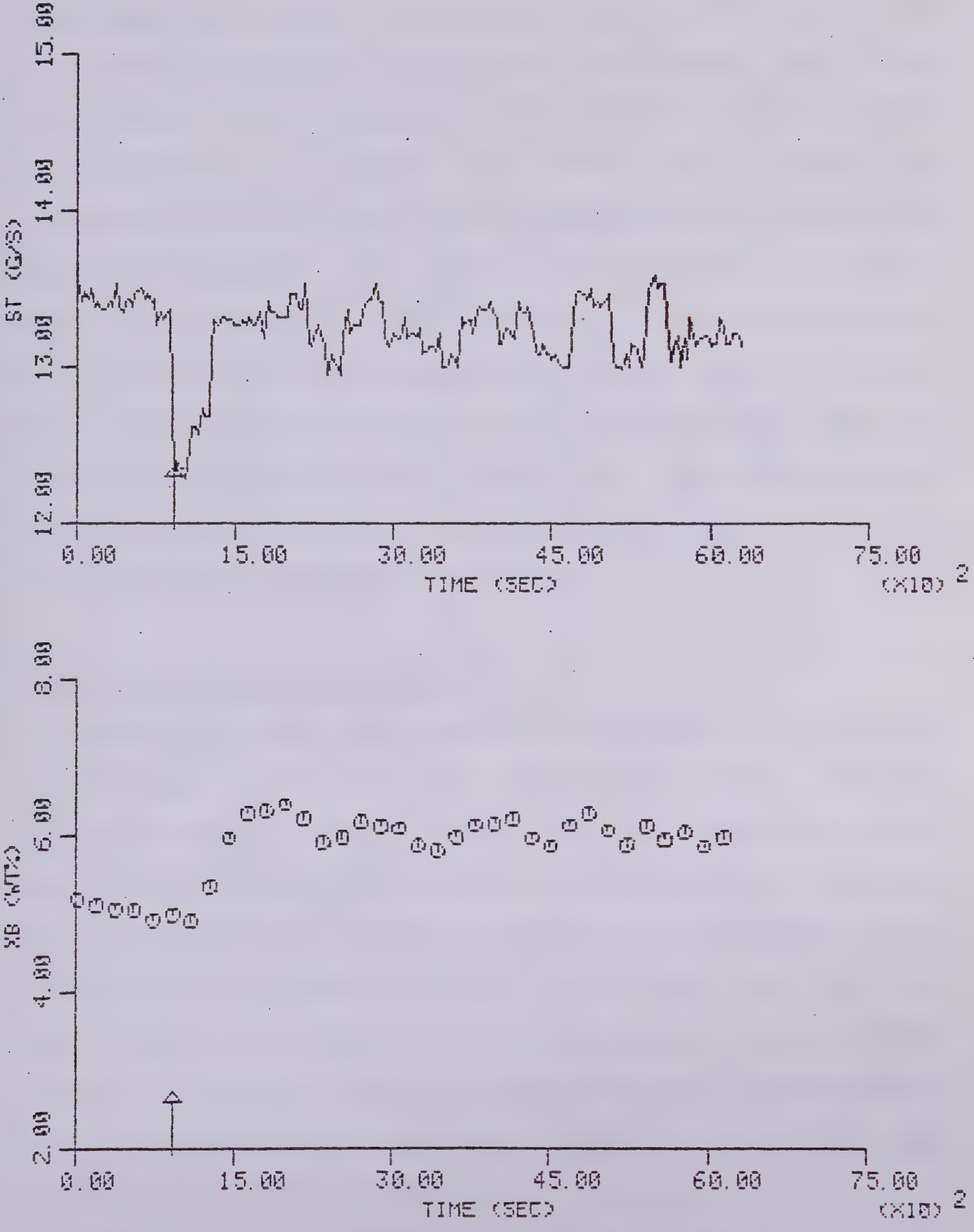


Figure 6.5.8 Smith Predictor Control of Bottom Composition for +1% Step Change in Set Point (Run E-SLP30 $K_p = -3.14$, $T_p = 918.0$, $T_d = 187.0$, $K_C = -0.869$, $K_I = -0.209$)

tion responses shown in Figures 6.5.1, 6 5.2, 6.5.5 and 6.5.6 which are more sluggish and oscillatory than those that resulted when using either the Dahlin or Smith predictor algorithms (cf. Figures 6.5.3, 6.5 4, 6.5.7 and 6.5 8). Furthermore control using the PI algorithm for a +1% step change in set point (cf. Figure 6 5.5) resulted in such an oscillatory response of the composition that such behaviour cannot considered to be acceptable. The IAE values in Tables 6.5.1 and 6.5.2 showed that the PID algorithm, with its derivative action provided a significant improvement in control performance compared to the PI algorithm for controlling processes containing time delay.

6.8 On-Line Tuning Techniques

The choice for the initial set of controller constants is important for any type of control application, with the selection of the initial tuning constants dependent on the user's knowledge of the process and the tuning technique. From the simulation studies, employing the improved tuning technique as outlined in Chapter 5, for the feed flow rate disturbances, it was found that the values of the model parameters used in the Dahlin algorithm were approximately the average values of the model parameters of the load and process transfer functions.

However, in the case of the online tuning of the Dahlin algorithm, the initial values of K_p and the T_d used in the algorithm were chosen to be the same values as those found

in the open loop transfer function of the process; the initial value of T_p in the algorithm was set to approximately the average value of the time constants in the load and process transfer functions. The desired closed loop time constant λ was initially set to be approximately 80% of the T_p of the process model used in the algorithm. From experience, these parameters ensure a stable start-up of the control loop. The tuning of the Dahlin algorithm proceeded by first adjusting the value of λ and then the values of K_p and T_p. A summary of the results obtained using the Dahlin algorithm is given in Table 6.6.1 and the composition responses are given in Figures 6.6.1 to 6.6.9.

As shown by the IAE values in Table 6.6.1, the performance of the Dahlin algorithm improved as the value of λ was decreased. Further minimization of the IAE value of the Dahlin algorithm resulted by applying the improved tuning procedure. As shown by the IAE values in the Table 6.6.1, the control performance improved gradually as the value of K_p was decreased while the value of T_p was increased. From Figures 6.6.5 to 6.6.9 and 6.4.3, it can be seen that the initial magnitude of change in the manipulated variable, in reaction to detection of the error, increased as the value of K_p was decreased. This behaviour is explained by the fact that the Dahlin algorithm, by virtue of the low value of K_p in the transfer function model (meaning that the bottom composition is insensitive to changes in steam flow rate) calculates a large correcting action in order to force the pro-

Table 6.6.1

Summary of Experimental Results for Dahlin Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate*

Run	K_p (wt.%/g/s)	T_p (s)	λ (s)	IAE (wt.% s)	Figure
E-DAH01	-5.63	750	605	15526	6.6.1
E-DAH02	-5.63	750	363	11874	6.6.2
E-DAH04	-5.63	750	234	10193	6.6.3
E-DAH05	-5.63	750	120	8529	6.6.4
E-DAH08	-5.06	750	164	8259	6.6.5
E-DAH09	-4.56	813	164	6961	6.6.6
E-DAH10	-3.87	853	164	5636	6.6.7
E-DAH11	-3.49	853	164	4663	6.6.8
E-DAH12	-3.14	918	164	4368	6.6.9
E-DAH13	-3.14	918	164	4253	6.4.3

* Td = 187s

cess to follow the desired closed loop response. Furthermore, it can be seen that the sluggishness of the composition response disappeared as the value of T_p in the Dahlin algorithm was increased. The reason for increasing the value of T_p is analogous to the strategy of decreasing the value of K_p. By virtue of the large value of T_p meaning that the Dahlin algorithm is controlling a slow process, the frequency of change in the manipulated variable has to be higher in order to force the process to follow the desired closed loop response as dictated by the algorithm.

In the case of tuning the Smith predictor, the final set of model parameters used in the Dahlin algorithm were also used in the Smith predictor therefore the tuning of the Smith predictor involved primarily adjusting the value of K_C and K_I. A summary of the experimental results achieved with the Smith predictor are given in Table 6.6.2. The bottom

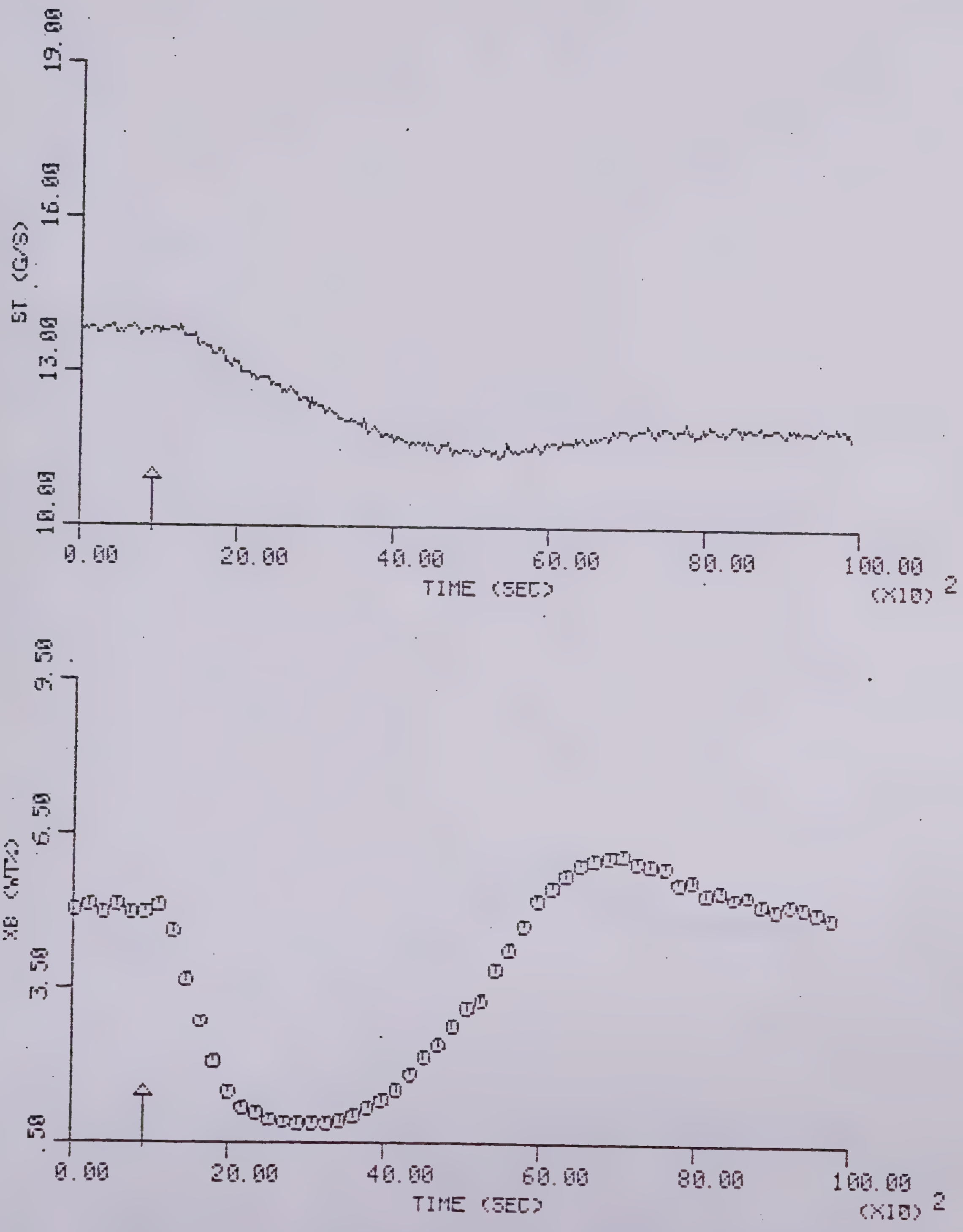


Figure 6.6.1 Dahlin Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-DAH01; $K_p = -5.63$, $T_p = 750.0$, $T_d = 187.0$, $\lambda = 605.0$)

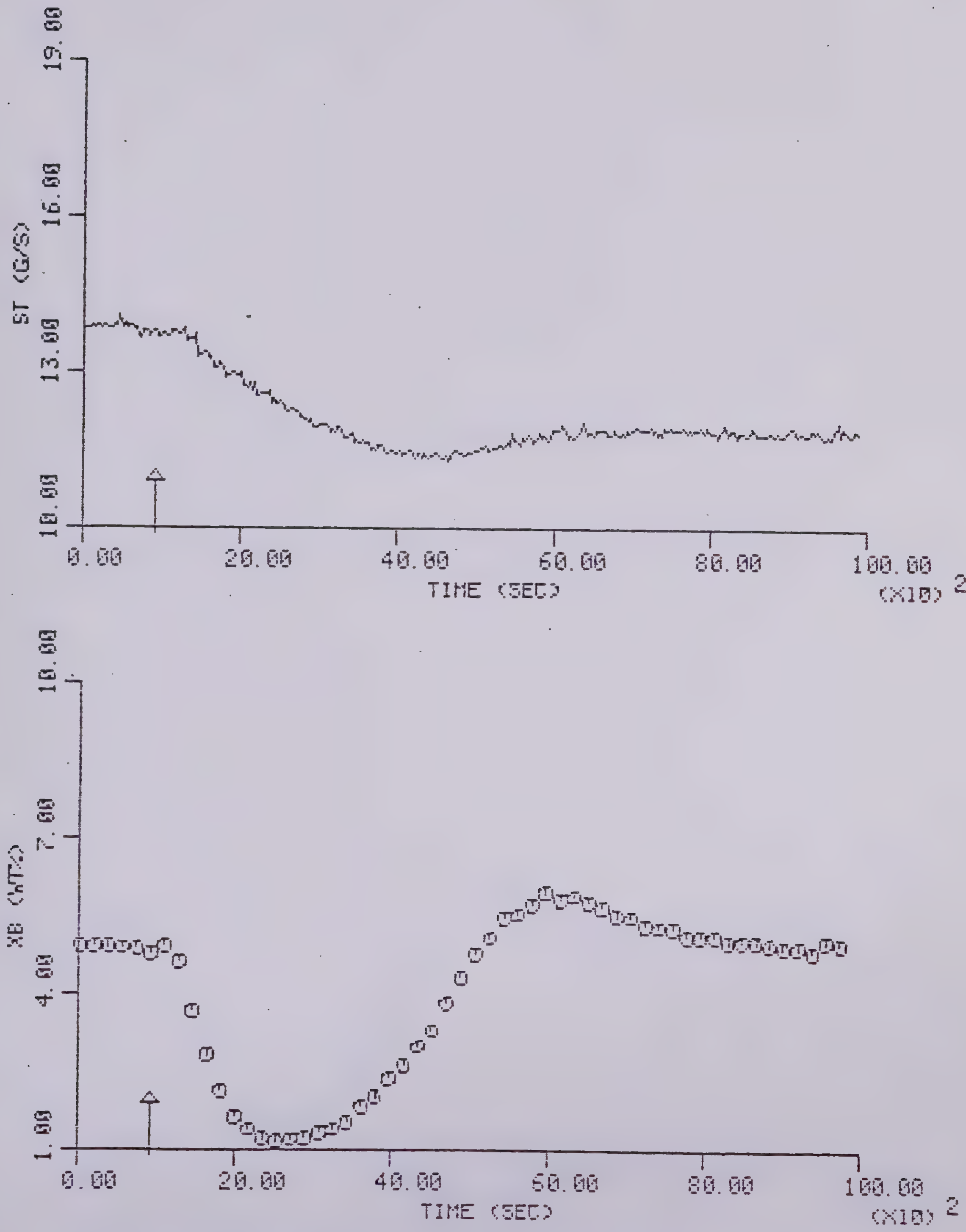


Figure 6.6.2 Dahlin Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-DAH02; $K_p = -5.63$, $T_p = 750.0$, $T_d = 187.0$, $\lambda = 363.0$)

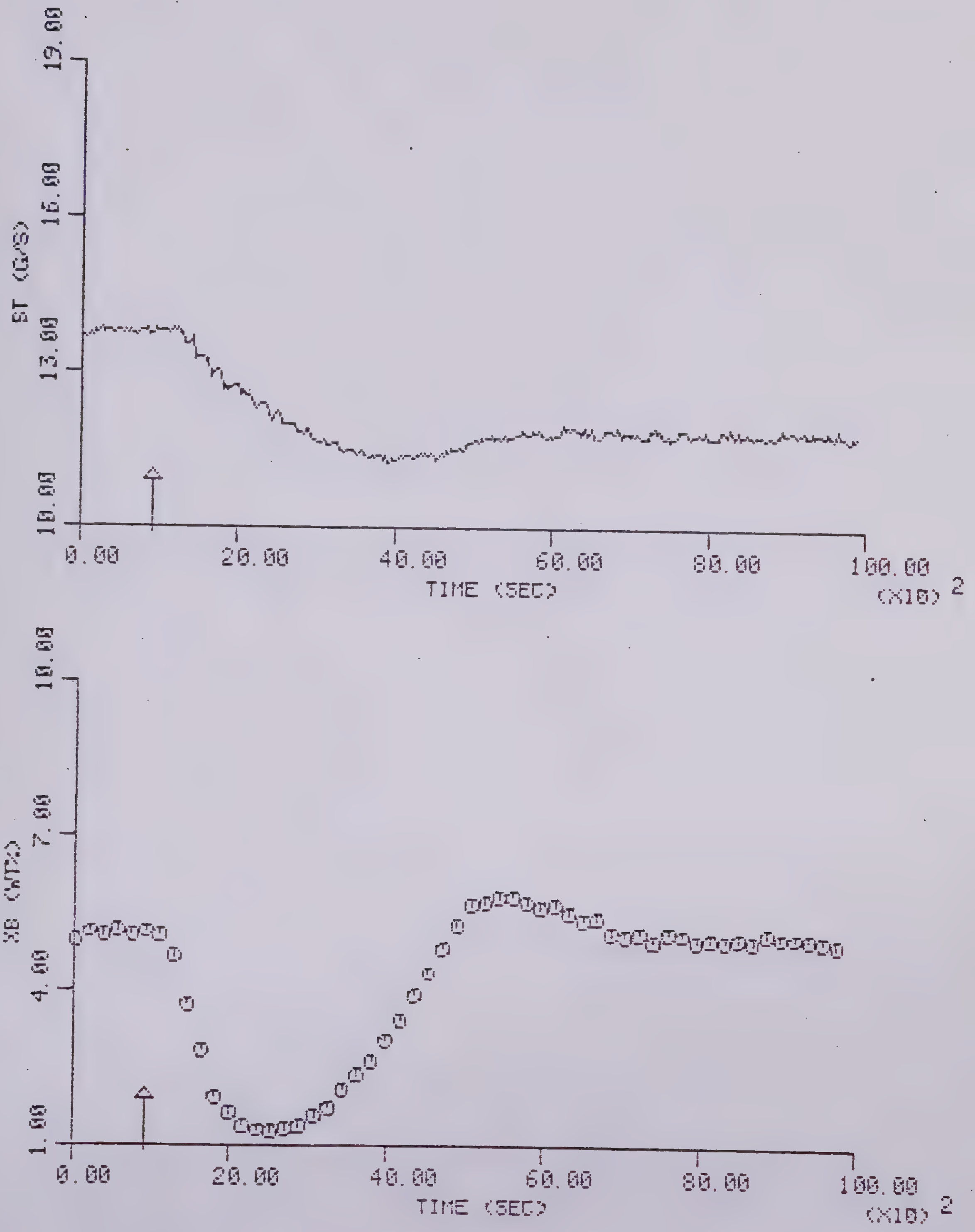


Figure 6.6.3 Dahlin Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-DAH04; K_p = -5.63, T_p = 750.0, T_d = 187.0, λ = 234.0)

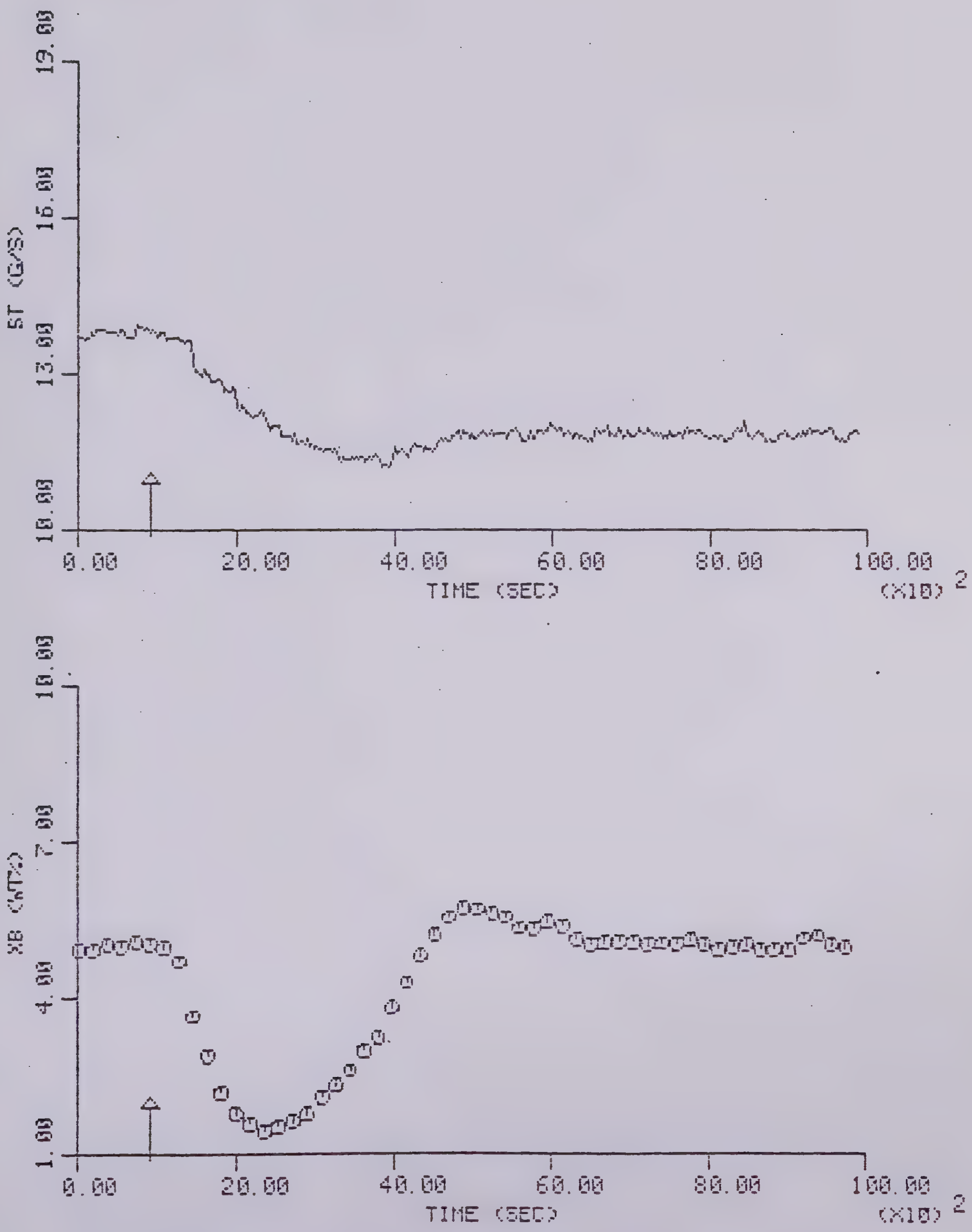


Figure 6.6.4 Dahlin Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-DAH05; $K_p = -5.63$, $T_p = 750.0$, $T_d = 187.0$, $\lambda = 120.0$)

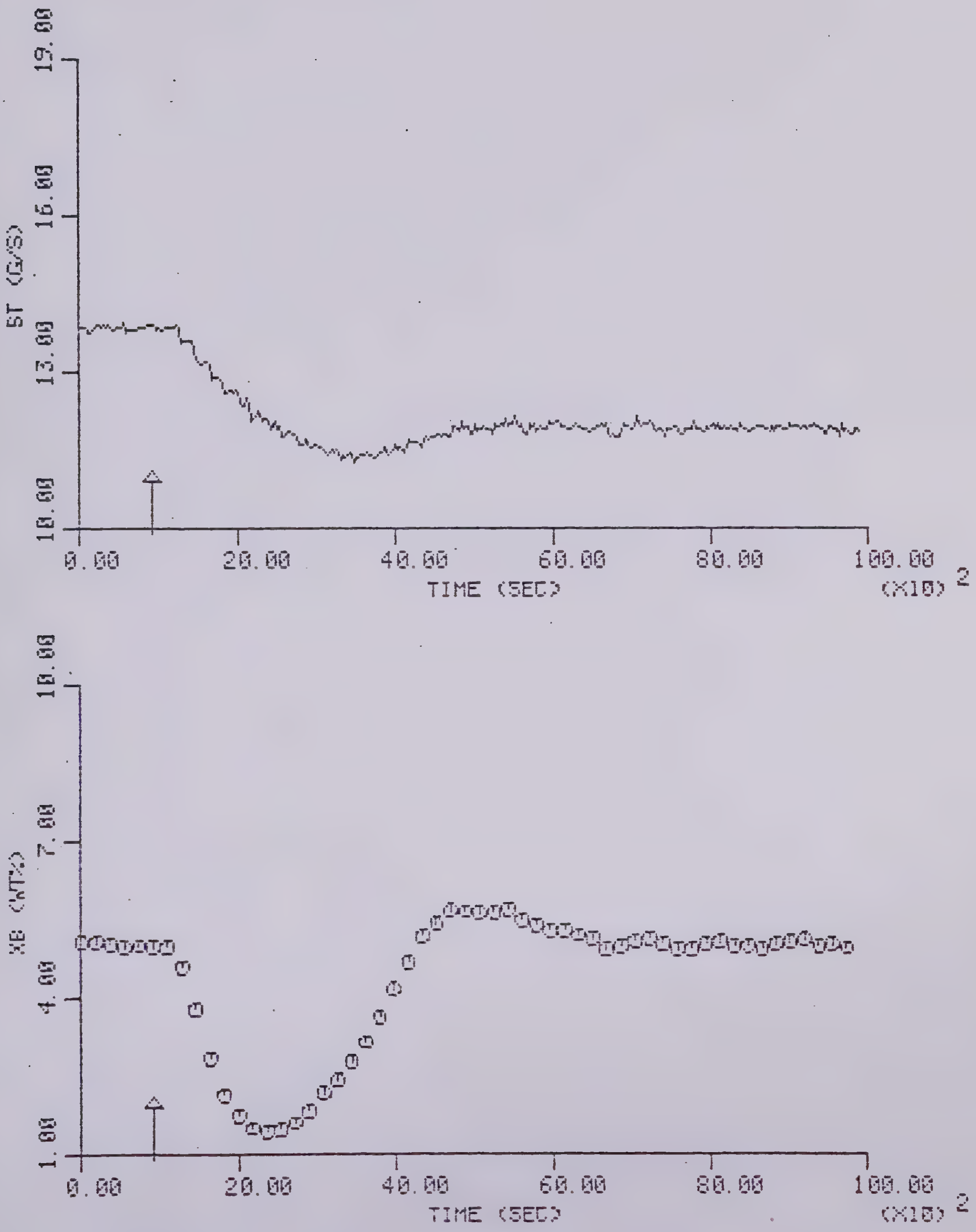


Figure 6.6.5 Dahlin Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-DAH08; $K_p = -5.06$, $T_p = 750.0$, $T_d = 187.0$, $\lambda = 164.0$)

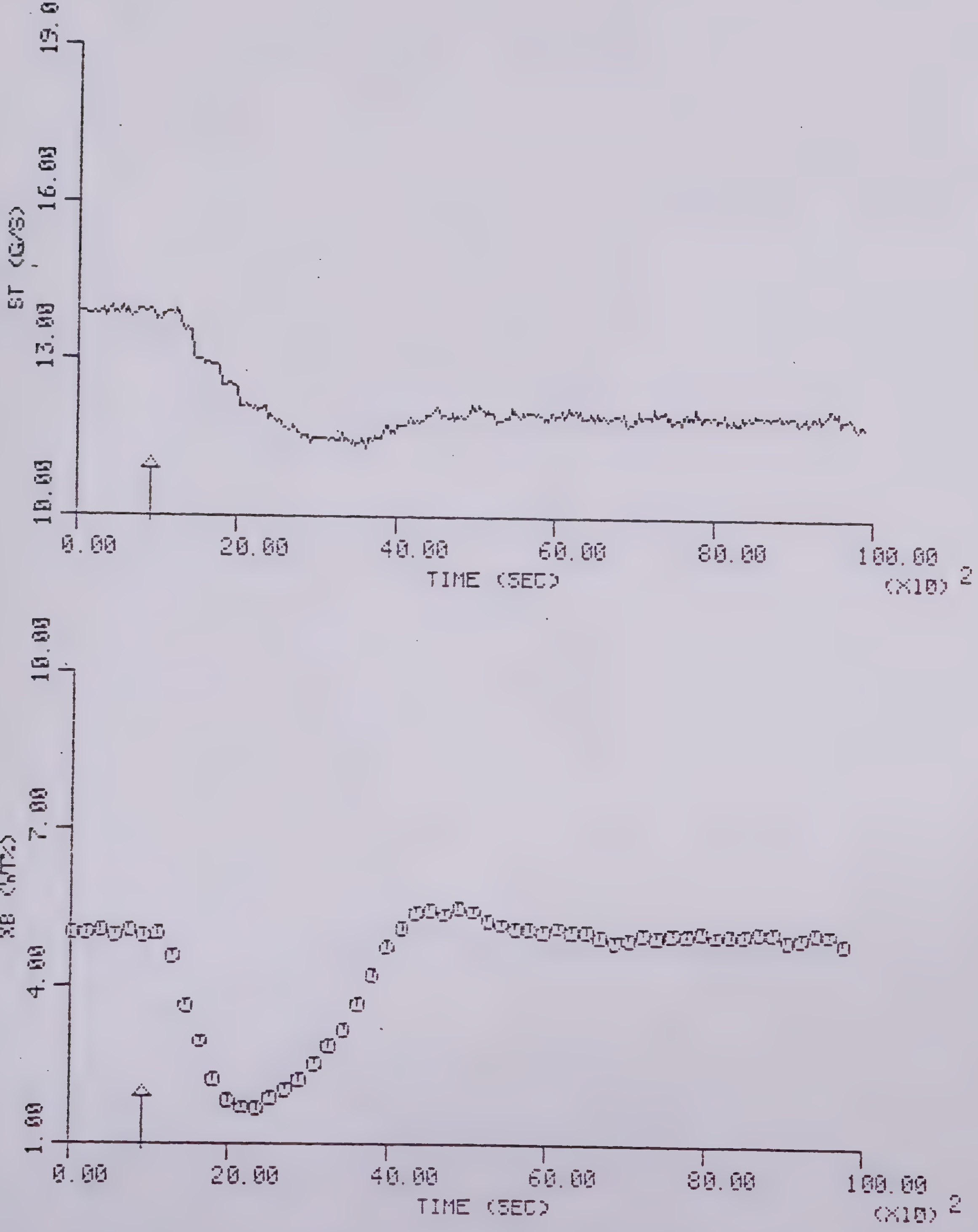


Figure 6.6.6 Dahlin Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-DAH09; K_p = -4.56, T_p = 813.0, T_d = 187.0, λ = 164.0)

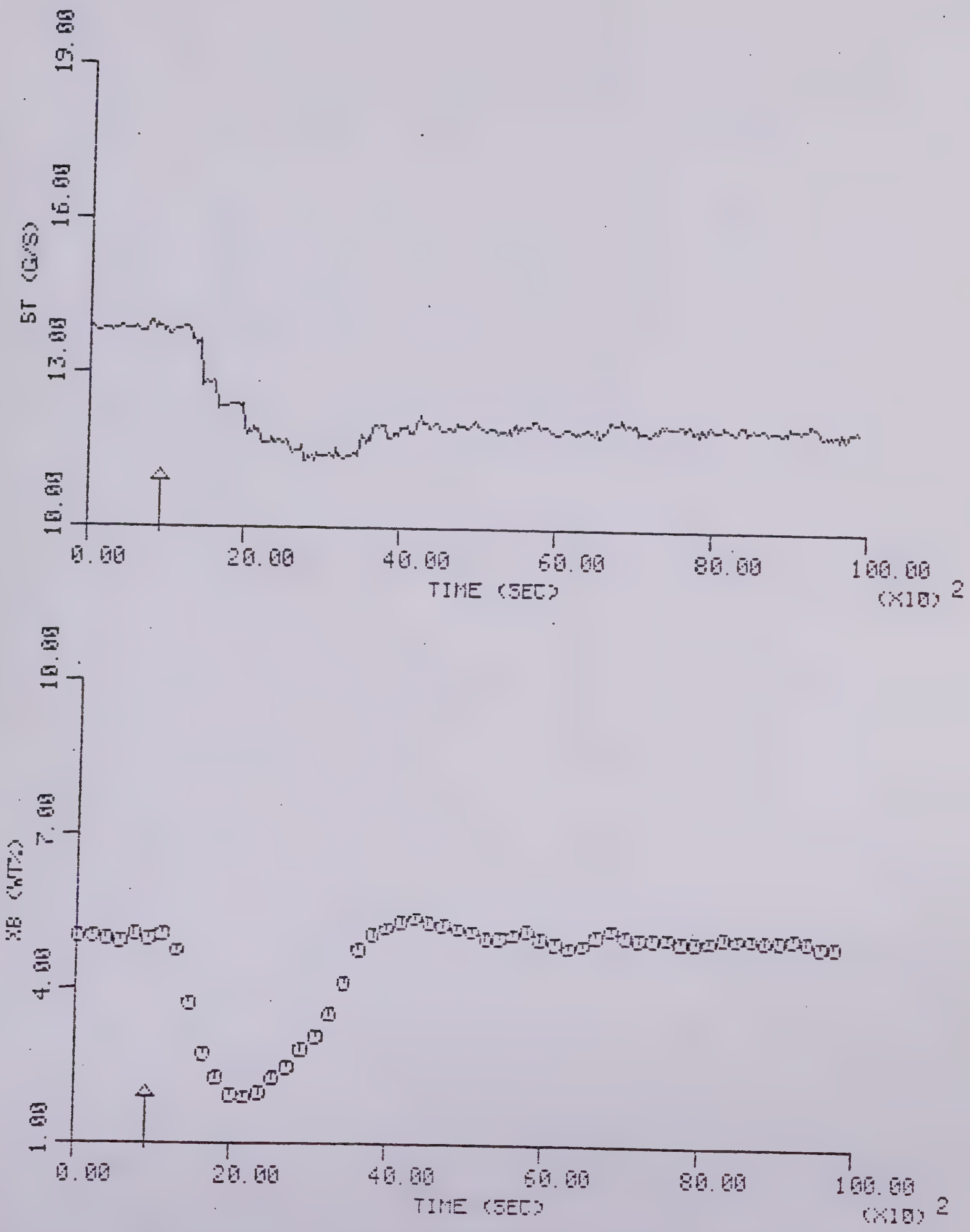


Figure 6.6.7 Dahlin Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-DAH10; $K_p = -3.87$, $T_p = 853.0$, $T_d = 187.0$, $\lambda = 164.0$)

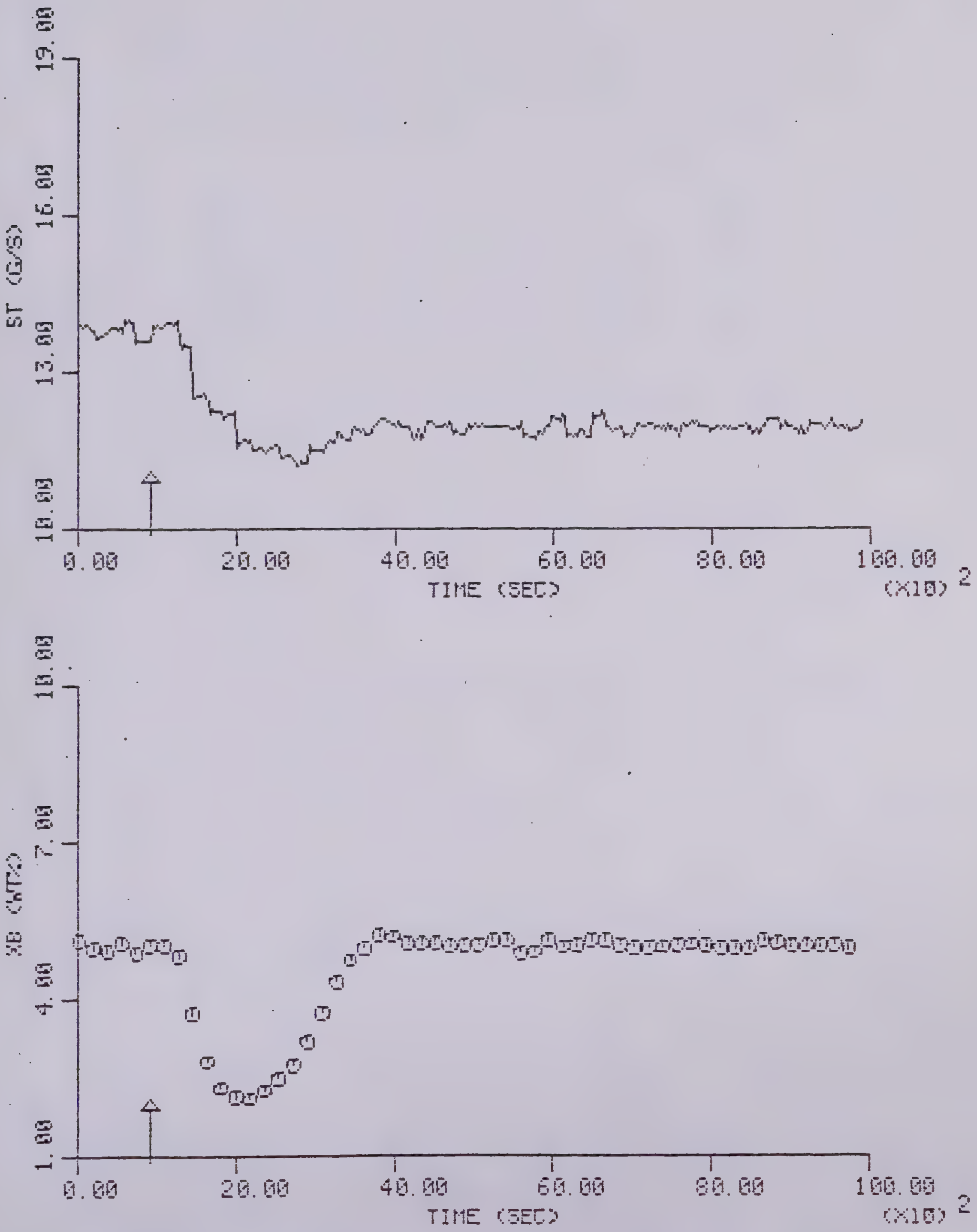


Figure 6.6.8 Dahlin Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-DAH11; $K_p = -3.49$, $T_p = 896.0$, $T_d = 187.0$, $\lambda_p = 164.0$)

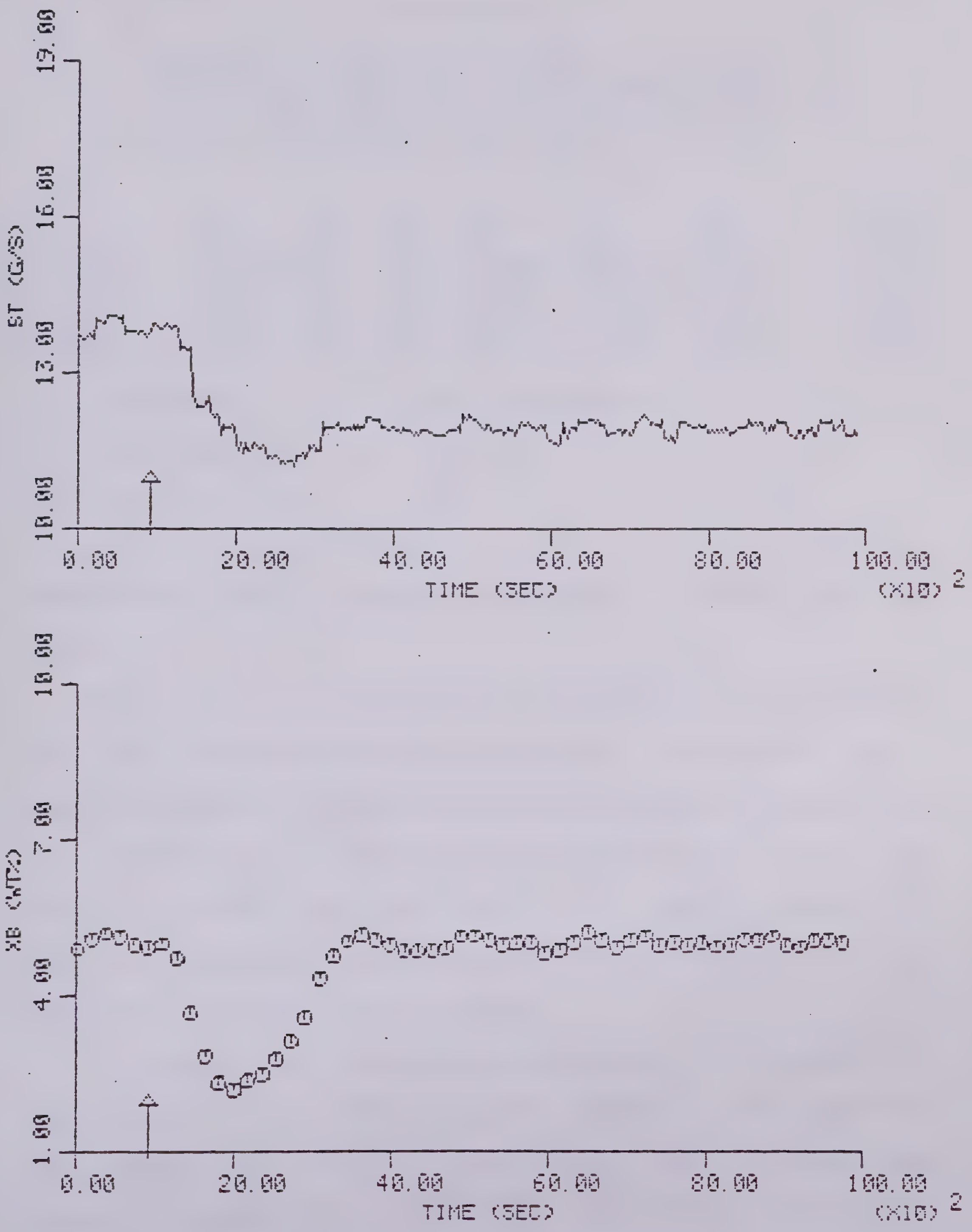


Figure 6.6.9 Dahlin Algorithm Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-DAH12; $K_p = -3.14$, $T_p = 918.0$, $T_d = 187.0$, $\lambda = 164.0$)

Table 6.6.2

Summary of Experimental Results for Smith Predictor Control of Bottom Composition for a -25% Step Change in Feed Flow Rate

Run	K_p	T_p	T_d	K_C	K_I	IAE	Figure
E-SLP09	-3.14	918	187	-0.830	-0.209	4609	6 6.10
E-SLP10	-3.14	918	187	-0.869	-0.209	4361	6.6.11
E-SLP19	-3.14	918	187	-0.711	-0.185	4549	6.6.12
E-SLP23	-0.27	872	187	-0.747	-0.213	4236	6.4.4

K_C = (g/s)/wt.%

K_I = (g/s)/(wt.%-s)

IAE = wt %-s

K_p = wt.%/(g/s)

T_p = s

T_d = s

composition control responses are given in Figures 6.6.10 to 6.6.12.

The tuning of the PI and PID algorithms was basically a trial and error procedure starting with the initial set of tuning constants calculated using the correlations of Smith (51). Summaries of some of the experimental results are given in Tables 6.6.3 and 6.6.4. The bottom composition responses obtained operating under PI and PID control are shown in Figures 6.6.13 to 6.6.20.

In common with any tuning procedure, the improved tuning procedure is a trial and error routine so the amount of time required to obtain a satisfactory set of tuning constants is dependent on the process being controlled as well as the experience of the individual performing the tuning. During the experimental evaluation of the tuning procedure for the Dahlin and PID algorithm, it was found that the

Table 6.6.3

Summary of Experimental Results for PID Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate

Run	K_C	K_I	K_D	IAE	Figure
E-PID05	-0.636	-0.200	-0.666	5236	6.6.13
E-PID09	-0.701	-0.105	-0.333	4554	6.6.14
E-PID13	-0.573	-0.100	-0.200	4558	6.6.15
E-PID15	-0.659	-0.110	-0.170	4986	6.6.16
E-PID21	-0.523	-0.117	-0.200	4477	6.4.2

K_C = (g/s)/wt.%

K_I = (g/s)/(wt.%-s)

K_D = (g/s)/(wt.%/s)

IAE = wt.%-s

Table 6.6.4

Summary of Experimental Results for PI Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate

Run	K_C	K_I	IAE	Figure
E-PI14	-0.551	-0.122	5850	6.6.17
E-PI18	-0.559	-0.111	5364	6.6.18
E-PI20	-0.551	-0.106	6534	6.6.19
E-PI22	-0.578	-0.100	6282	6.6.20
E-PI24	-0.607	-0.095	5148	6.4.1

K_C = (g/s)/wt.%

K_I = (g/s)/(wt.%-s)

IAE = wt.%-s

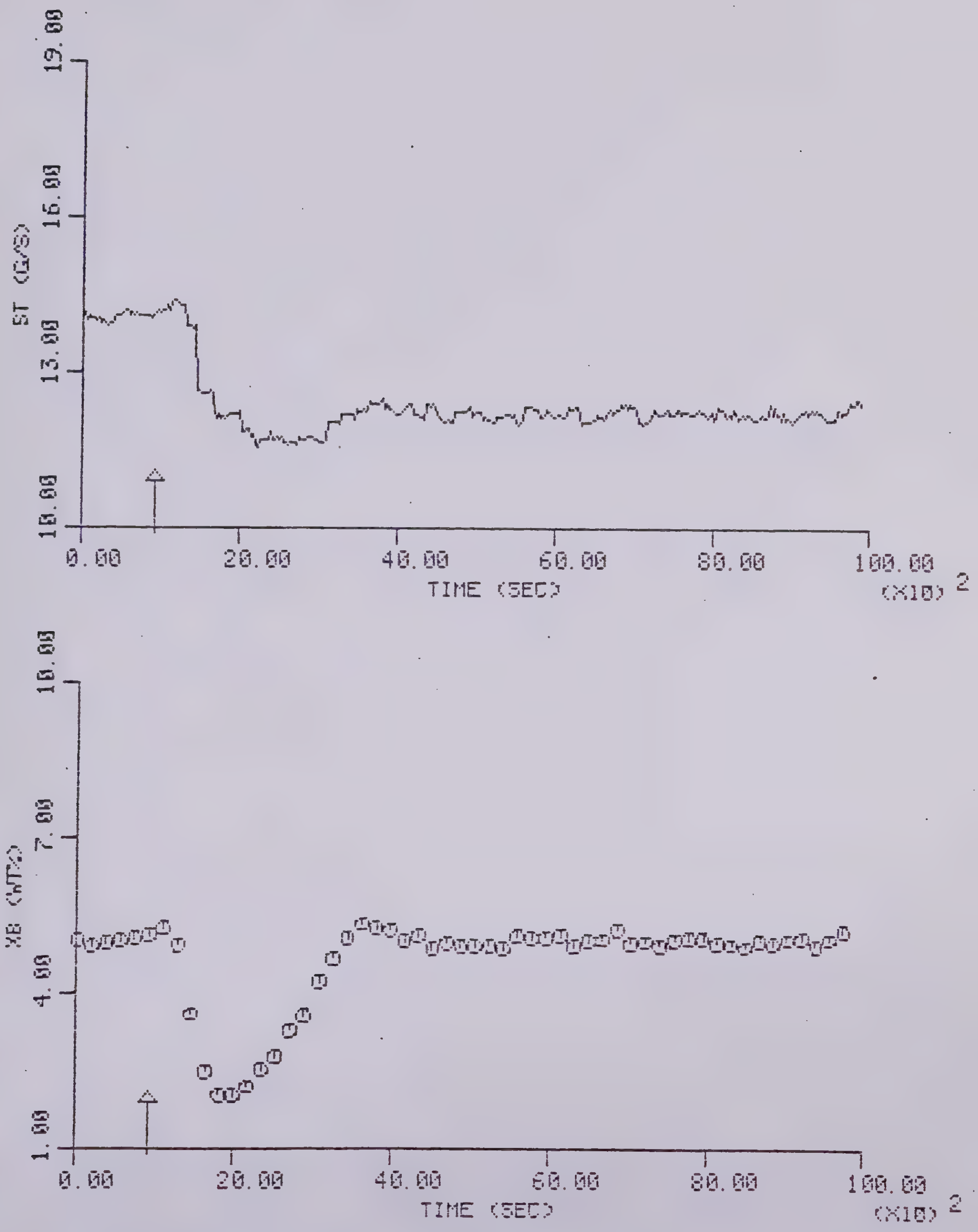


Figure 6.6.10 Smith Predictor Control for Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-SLP09; $K_p = -3.14$, $T_p = 918.0$, $T_d = 187.0$, $K_C = -0.830$, $K_I = -0.209$)

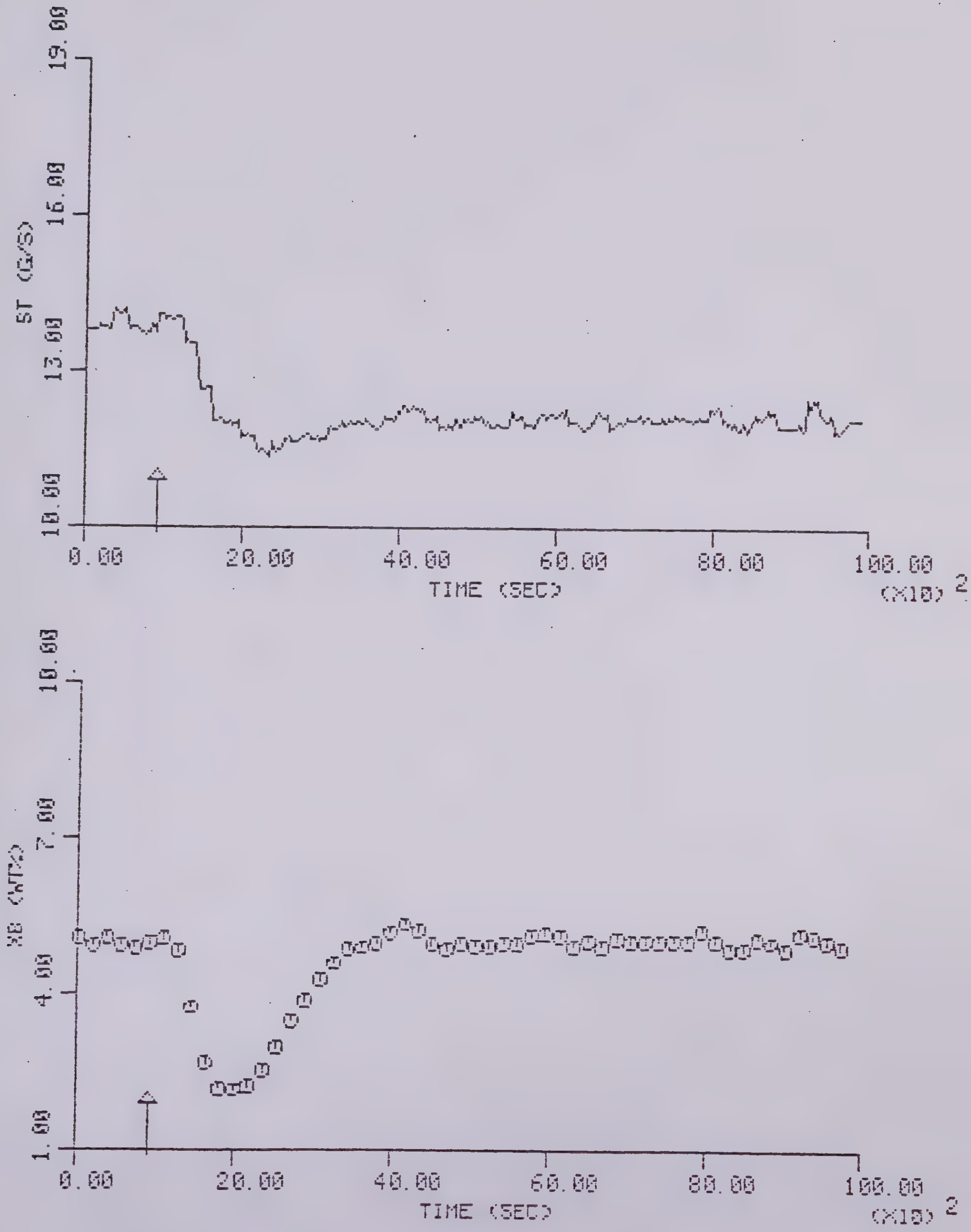


Figure 6.6.11 Smith Predictor Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-SLP10; K_p = -3.14, T_p = 918.0, T_d = 187.0, K_C = -0.869, K_I = -0.209)

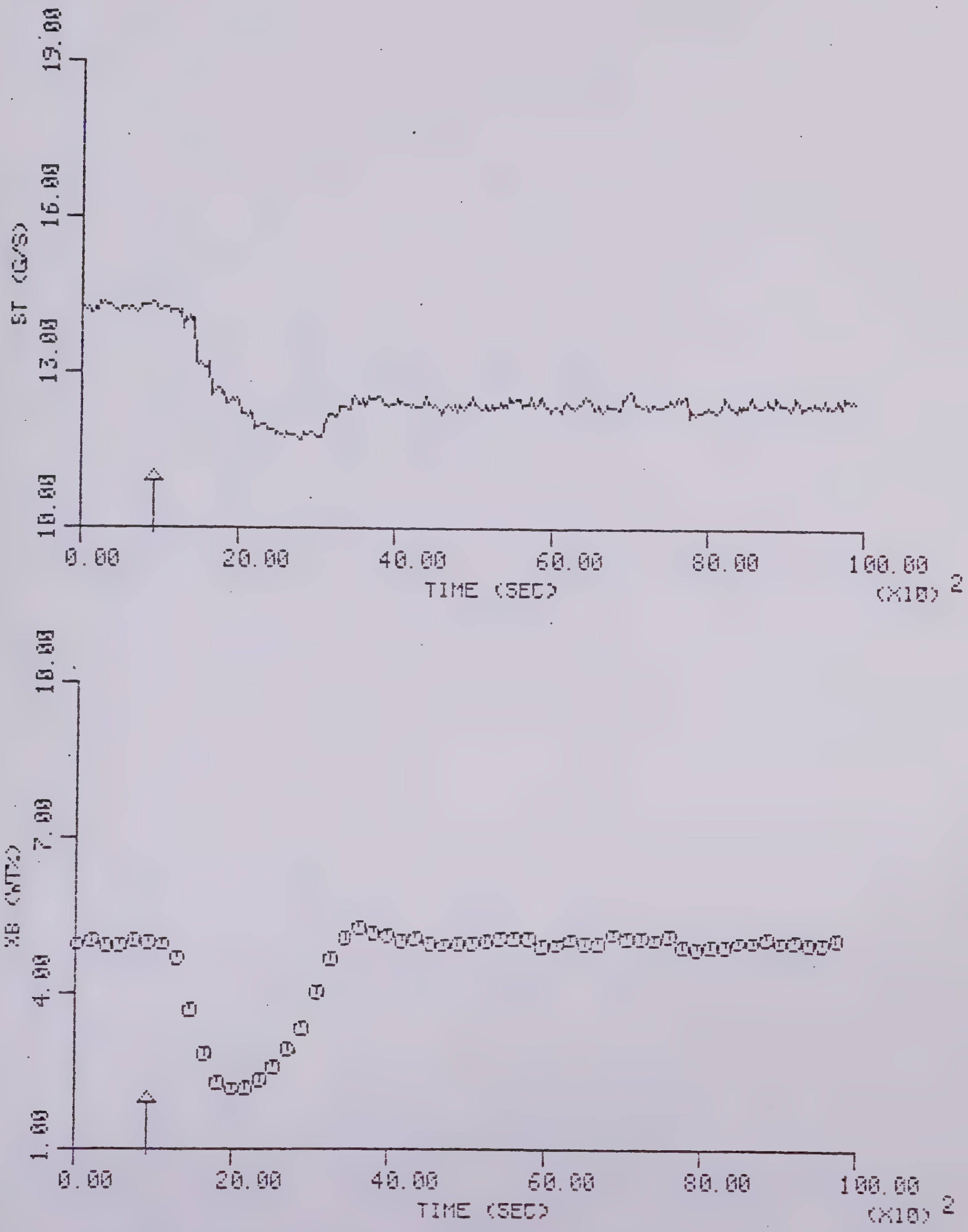
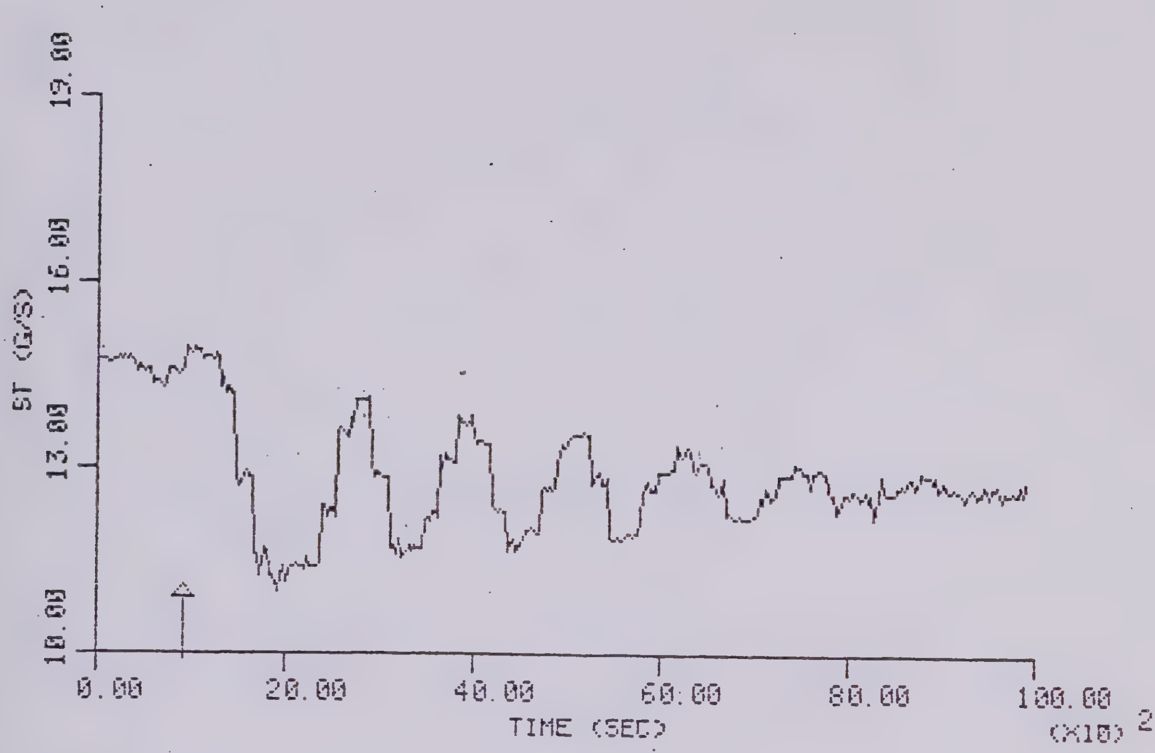


Figure 6.6.12 Smith Predictor Control of Bottom Composition for -25% Step Change in Feed Flow Rate (Run E-SLP19; K_p = -3.14, T_p = 918.0, T_d = 187.0, K_C = -0.711, K_I = -0.185)



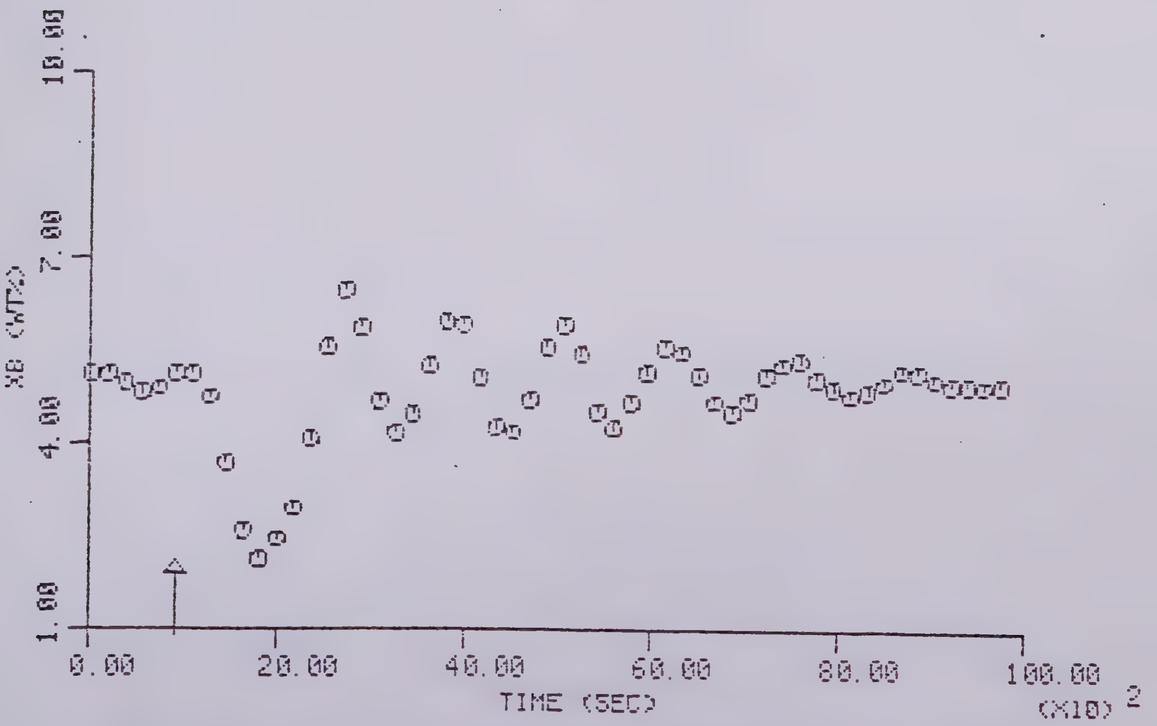


Figure 6.6.13 PID Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (Run E-PID05; K_C= -0.636, K_I= -0.200, K_D= -0.666)

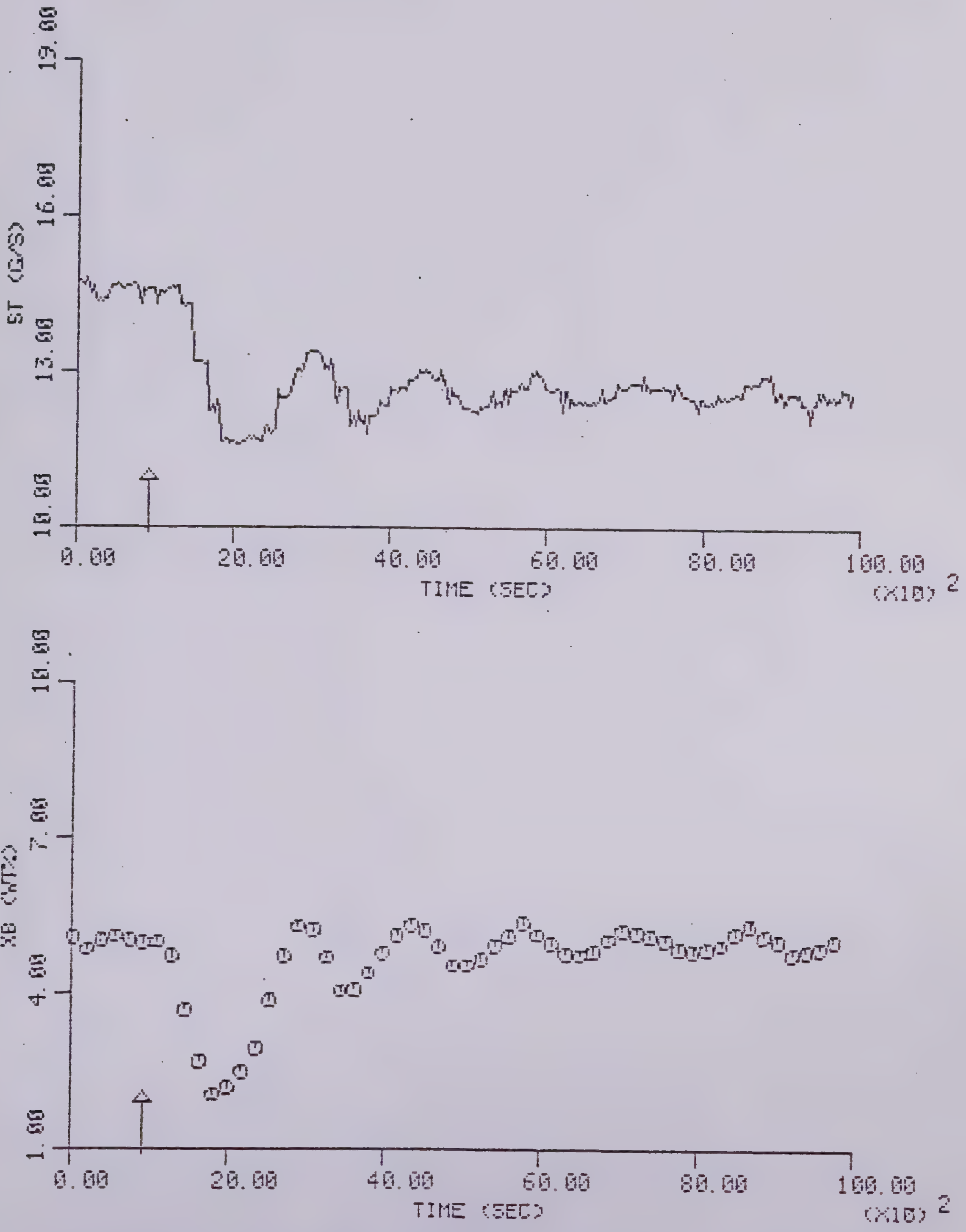


Figure 6.6.14 PID Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (Run E-PID09; K_C= -0.701, K_I= -0.105, K_D= -0.333)

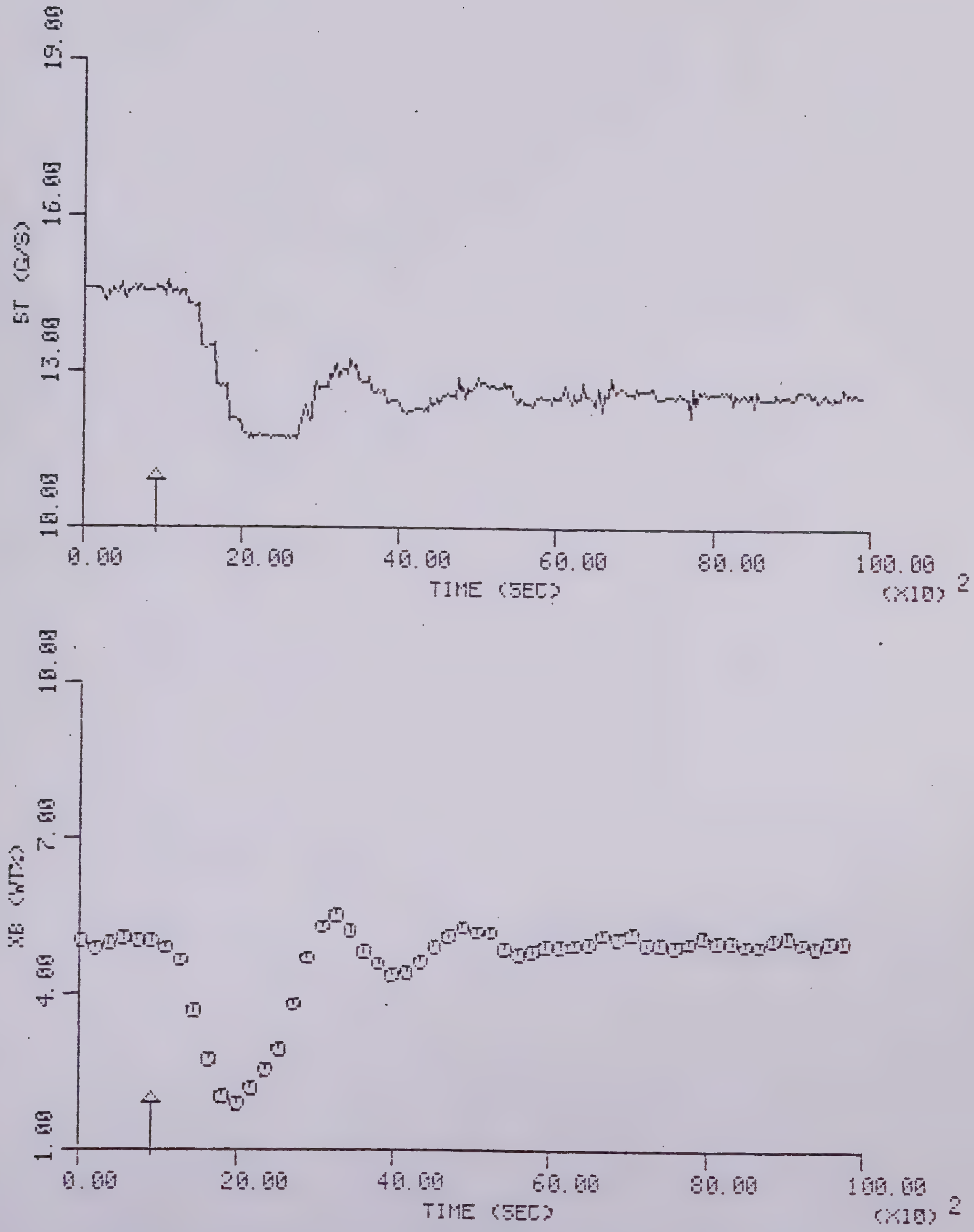


Figure 6.6.15 PID Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (Run E-PID13; $K_C = -0.573$, $K_I = -0.100$, $K_D = -0.200$)

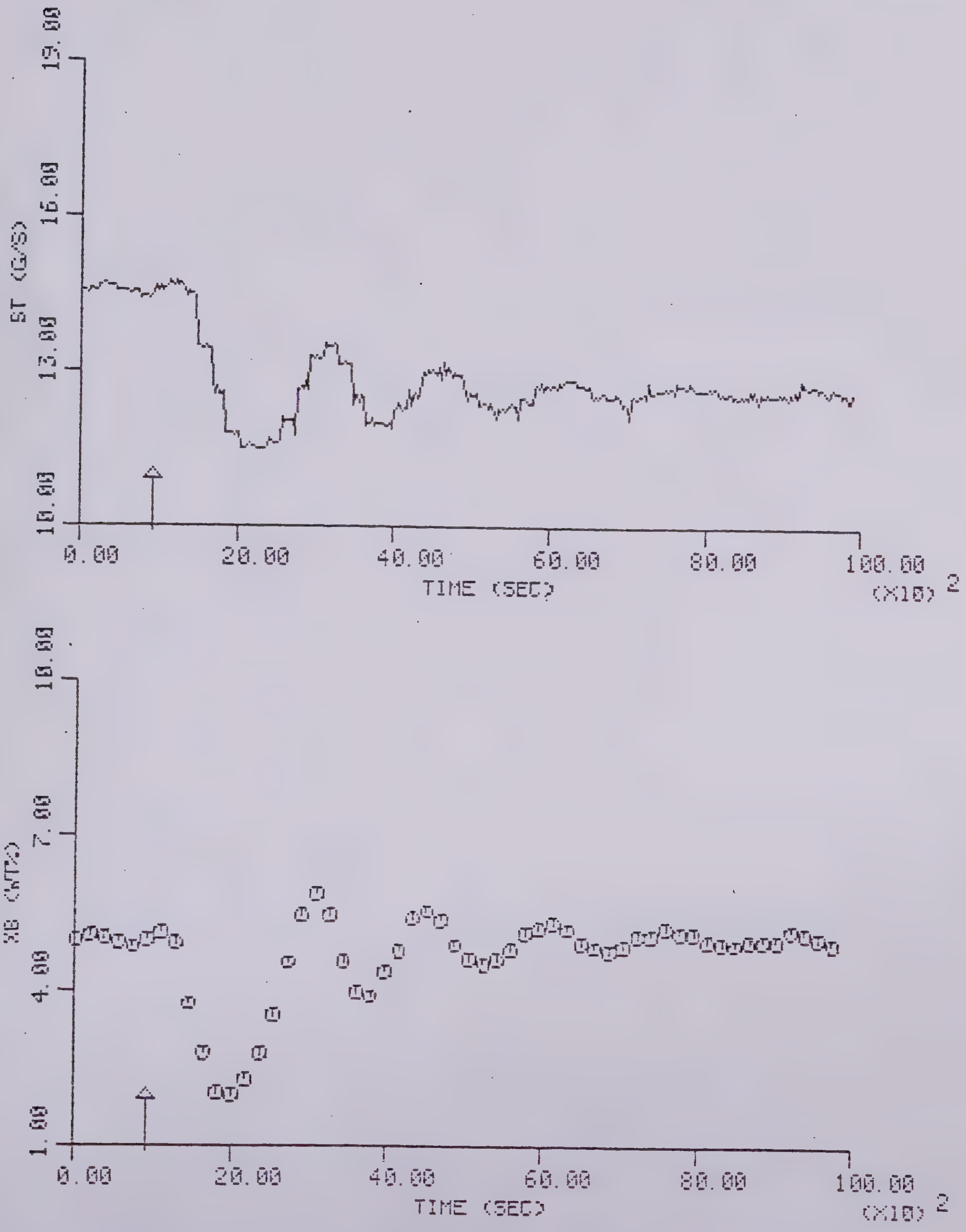


Figure 6.6.16 PID Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (Run E-PID15; K_C= -0.659, K_I= -0.110, K_D= -0.170)

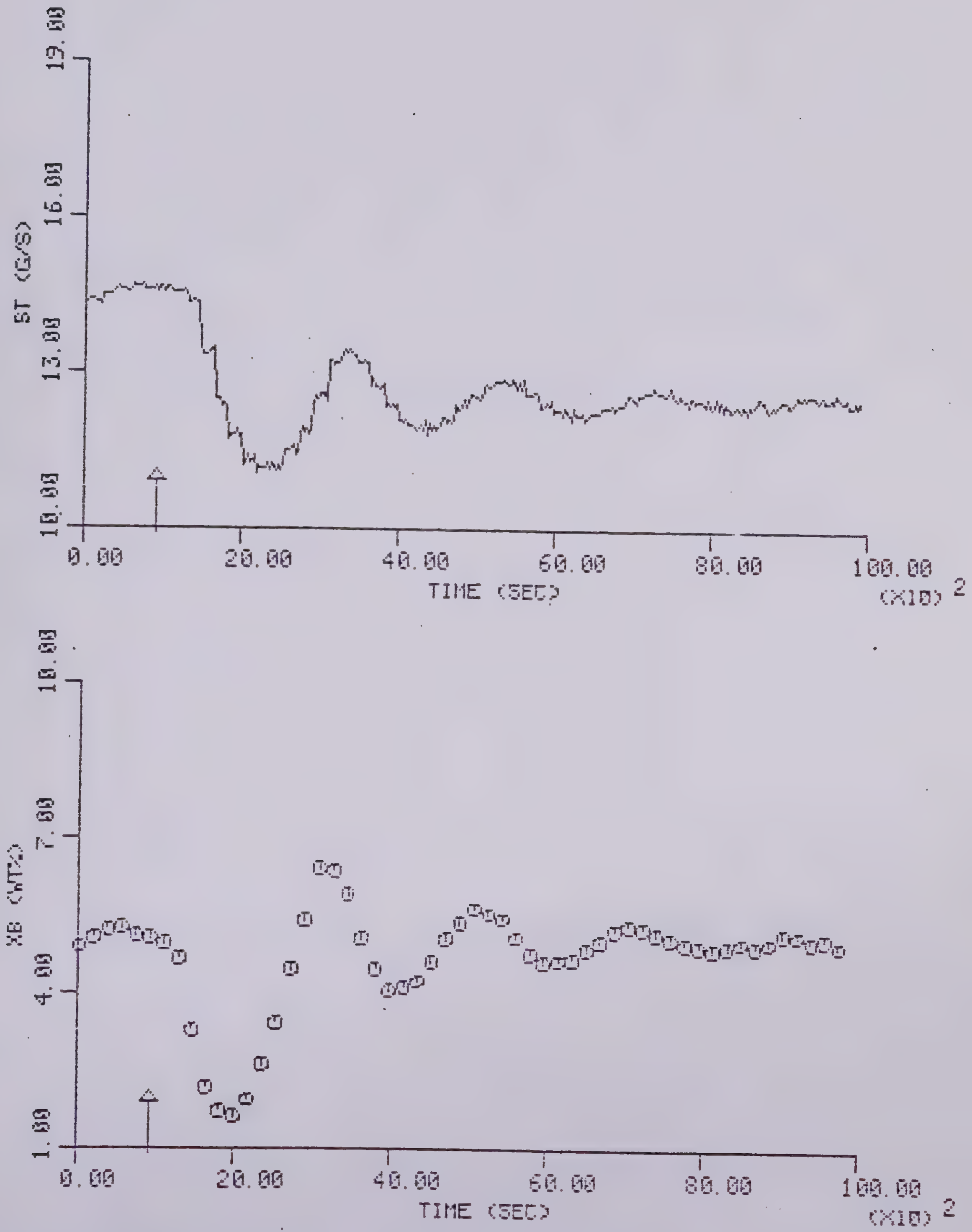


Figure 6.6.17 PI Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (Run E-PI14; $K_C = -0.551$, $K_I = -0.122$)

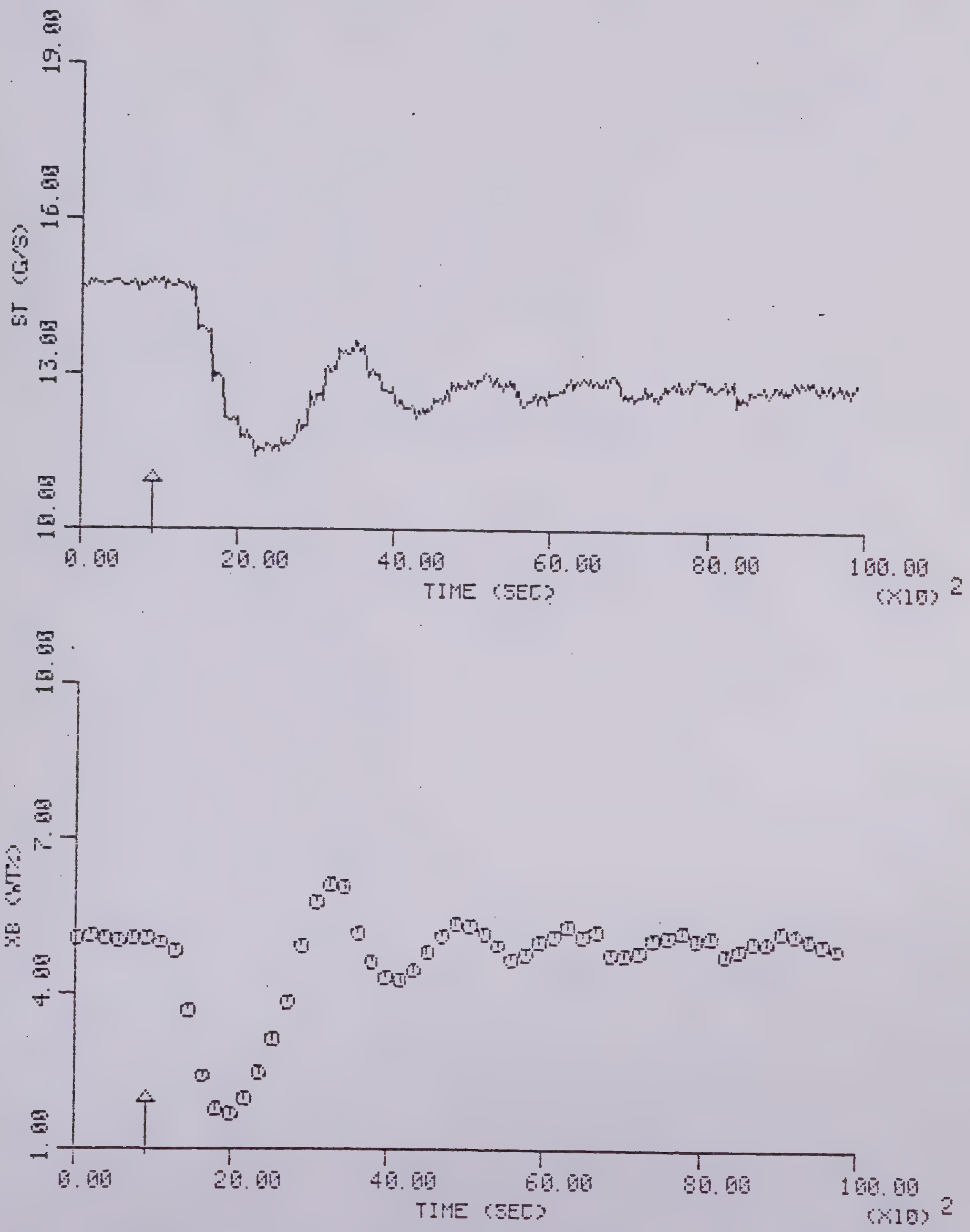


Figure 6.6.18 PI Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (Run E-PI18; $K_C = -0.559$, $K_I = -0.111$)

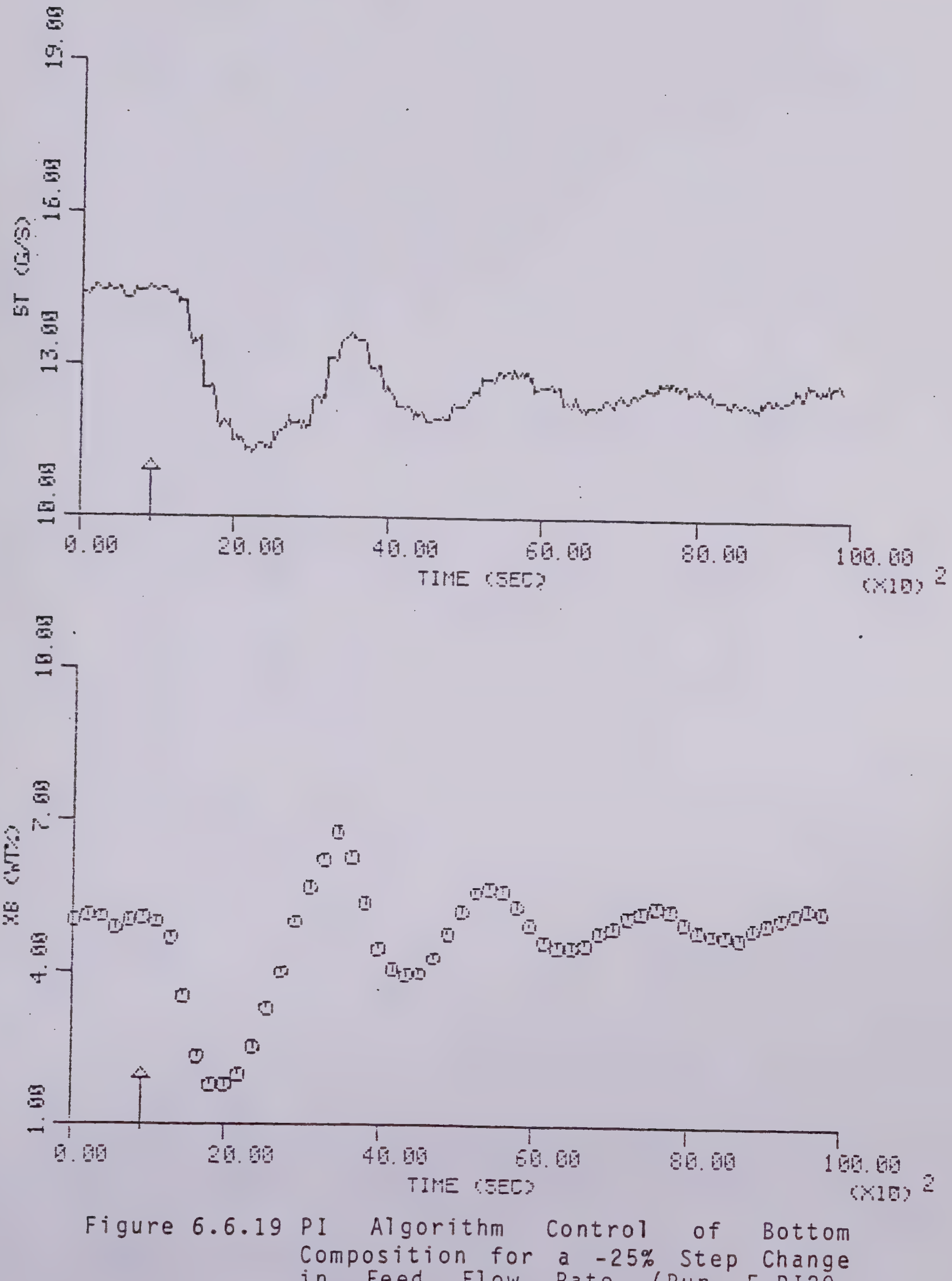


Figure 6.6.19 PI Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (Run E-PI20; $K_C = -0.551$, $K_I = -0.106$)

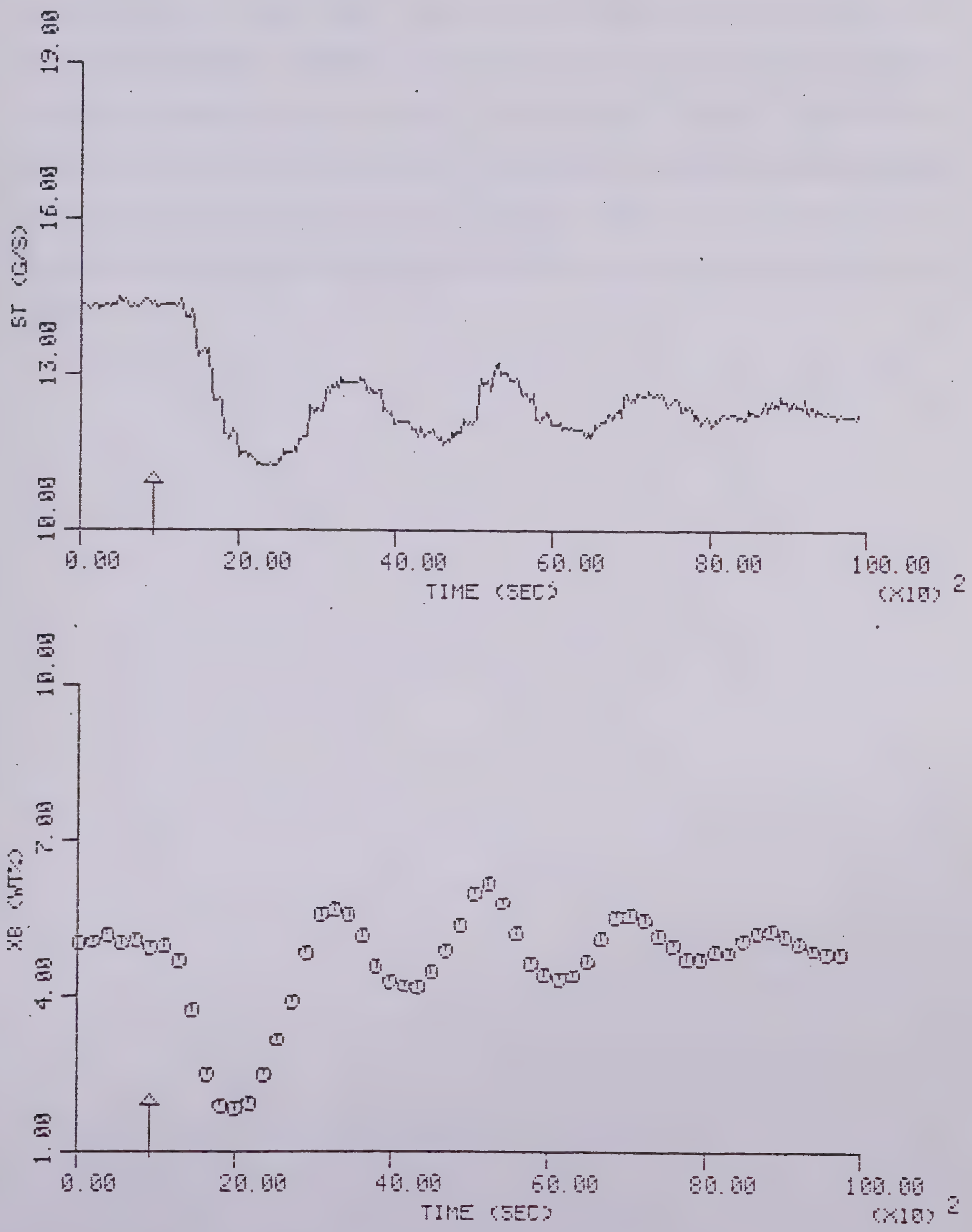


Figure 6.6.20 PI Algorithm Control of Bottom Composition for a -25% Step Change in Feed Flow Rate (Run E-PI22; K_C = -0.578, K_I = -0.100)

amount of time required to tune the Dahlin algorithm was comparable to the time required for the PID algorithm to yield a similar control performance. However, the Dahlin algorithm would tend to be favoured by control engineers because of the nonoscillatory responses of both manipulated and controlled variables (cf. Figure 6.4.3) as compared to those that result from using the PID algorithm (cf. Figure 6.4.2).

7. Conclusions and Recommendations

From the digital simulation studies, the following conclusions can be drawn:

1. The nonlinear distillation column model as developed by Bilec (4) and subsequently modified in this study provided a satisfactory representation of the dynamics of the distillation column.
2. First order time delay transfer function models provide a satisfactory representation of the column dynamics for control purposes.
3. In the case of set point changes, the deadbeat, Dahlin and Smith predictor algorithms with only minimal model errors provided improved control performance compared to that achieved using the discrete PI and PID algorithms.
4. For changes in feed flow rate, especially when the dynamic of this disturbance is much faster than that of the process, the deadbeat, Dahlin and Smith predictor algorithms tuned by using conventional tuning methods failed to provide satisfactory performance compared to that achieved using PI and PID algorithms.
5. Although the deadbeat algorithm does not have any provision for on-line tuning of parameters in the conventional sense, the process model parameters

used in the algorithm can be used as on-line tuning parameters.

6. The above strategy can also be applied to the Dahlin and Smith predictor algorithms especially when these algorithms are applied for regulatory control operation.
7. Use of derivative action, that is using the PID algorithm instead of the PI algorithm, significantly improved the control performance for either servo or regulatory control operation.

From the experimental results, the following conclusions can be drawn:

1. For regulatory control, the control performance achieved using the Dahlin and Smith predictor algorithms tuned by using the improved tuning procedure, was much better than was possible using the PI algorithm. However, with the proper tuning, the performance achieved using the PID algorithm was found to be comparable to that achieved using the Dahlin and Smith predictor algorithms.
2. For set point changes, control using the Dahlin and Smith predictor algorithms with the tuning constants used for regulatory control provided superior control performance to that achieved using the PI and PID algorithms.
3. The results confirmed the simulated results that the control behaviour using the PID algorithm is much

better than is possible using the PI algorithm for both servo and regulatory control. This demonstrates the effectiveness of derivative action on the control of processes containing time delay.

Recommendations for future work suggested by this study include the following:

1. From the design procedure for the Dahlin algorithm, it can be seen that this algorithm is designed primarily for servo control operation. Although it provides satisfactory performance for regulatory control operation when it is tuned by using the improved tuning technique, it is more appropriate to include the load transfer function model in the design procedure if regulatory control operation is the primary concern.
2. Similarly, if the Smith predictor is used for controlling systems subjected to frequent load disturbances, load prediction as suggested by Meyer (38) should be incorporated in the control algorithm.
3. Other digital control algorithms which employ design techniques that are similar to the direct synthesis method and have the form of Equation 3.1 1, such as the Kalman algorithm (10), should be studied and compared with the PID algorithm to access their performance for controlling time delay processes.
4. Since the deadbeat, Dahlin and Smith predictor control algorithms are model dependent, the control

performance of these algorithms using a higher order transfer function model in the algorithm synthesis should be studied.

5. Since the performance of these algorithms depends on the accuracy of the parameters of the process transfer function model, it is suggested that an on-line parameter estimation scheme which will operate in a supervisory mode should be incorporated into the algorithms. This scheme could easily be implemented using DISCO. At each sampling time, the parameter estimation scheme would calculate the parameters used in the transfer function model and the coefficients of the control algorithm will then be calculated subsequently and transferred back to the DISCO data base. Then, the control output would be calculated based on the new coefficients and the error and output sequences. The advantage of this approach compared to that using a parameter invariant model is that it would account for changes in process dynamics due to disturbances.

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